

7th NATIONAL LEVEL STUDENT CONFERENCE

IEEE TECHNICOKNOCKDOWN-2026

TKD-26

ORGANIZED BY DEPARTMENT OF E&TC ENGG. SIT LONAVALA

TECHNICALLY SPONSORED BY
IEEE MAHARASHTRA SECTION & IETE PUNE CENTRE

THEME: CLEAN AND GREEN VILLAGE: RURAL TRANSFORMATION



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(TKD-26)

(April 18, 2026)

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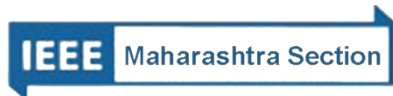
Sinhgad Institutes

Department of E&TC Engineering
Sinhgad Institute of Technology, Lonavala

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IEEE TKD-26

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7th National Level Student Conference



"IEEE TECHNICOKNOCKDOWN-2026 (TKD-26)"

Organized by Department of E&TC Engg, SIT Lonavala



Technically Sponsored by IEEE Maharashtra Section and IETE, Pune Local Center Supported by IEEE SITSB & IETEISF, SIT Lonavala

Saturday, April 18, 2026

(Online mode)



Theme: Clean and Green Village: Rural Transformation



Chief Patron

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Welcome to

TECHNICOKNOCKDOWN-2026

It is our great pleasure to welcome you all for the 7th virtual “TECHNICOKNOCKDOWN-2026 (TKD-26)” National Level Students Conference for technical paper presentation on April 18, 2026. The TKD-26 is organized by Department of Electronics and Telecommunication Engg, Sinhgad Institutes of Technology, Lonavala, Pune, Maharashtra. The conference is technically sponsored by IEEE Maharashtra Section and IETE, Pune local center and supported by IEEE SITSB and IETEISF, SIT Lonavala. TKD-26 provides an ideal platform for exchange of ideas among researchers, students, and practitioners.

TKD-26 has received more than 112 papers from all over India in 8 different tracks including, Internet of Things (IoT), Artificial Intelligence and Machine Learning, Cyber Security and Privacy, Next Generation Network, Sensor Networks and Smart Application, Electrical Vehicle, Robotics and Automation,. After a Peer Review Process 56 papers are selected for the oral presentations and finally 32 papers are registered. The registered and presented papers are published in IEEE TKD-26 proceeding with ISBN No. 978-81-992245-2-9

We hope that you will find this event interesting and thought provoking. TKD-26 will provide you with a valuable opportunity to share ideas with other researchers, students, and practitioners from institutions. We look forward to the contribution towards the event and see you virtually.

Team
TECHNICOKNOCKDOWN-2026

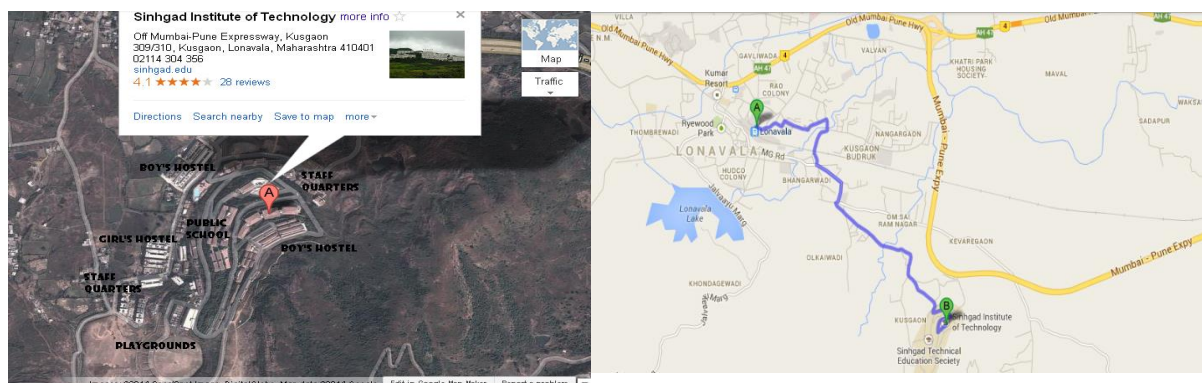
About STES:

Sinhgad Technical Education Society (STES) was set up in August 1993, under the able and dynamic leadership of Prof. M.N. Navale with an objective of providing quality education in the field of Engineering, Dentistry, Management, Computer, Pharmacy, Architecture, Hotel Management and the basic school education from kinder garden onwards. There are 58 institutes under the aegis of STES offering full-fledged school education, Diploma, Graduation, Post-Graduation courses and Ph.D. programs in various branches of Engineering, Science and Management at five educational campuses ideally located in pollution free lush green and picturesque environment conducive for learning. (sit.sinhgad.edu).

About SIT, Lonavala

Sinhgad Institute of Technology (SIT), Lonavala since its establishment in 2004 is involved in practicing teaching-learning methodologies of excellence to deliver quality engineering education for students all over India. The institute is housed in beautiful surroundings, fully residential campus of 220 acres on Pune-Mumbai expressway at Lonavala. Academic discipline with space for individual innovations, emphasis on life skill development of students, 'willing to work' team of faculty members and initiative for Industry interface, have been the silent activity of the college. Institute has following branches; The Institute is accredited by NAAC with Grade "A"

1. E&TC, Engineering
2. Mechanical Engineering,
3. Electrical Engineering,
4. Computer Engineering,
5. Information Technology &
6. Masters in Electrical and Power Systems





Vision and Mission of the Institute

VISION

उत्तमपुरुषान् उत्तमाभियंतृन् निर्मातुं कटीबध्दाः वयम्।

We are committed to produce not only good engineers but good human beings, also.

MISSION

Holistic development of students and teachers. We strive to achieve this by imbibing a unique value system, transparent work culture, excellent academic and physical environment conducive to learning, creativity and technology transfer.

Quality Policy

Quality Policy is aimed at achieving excellence in Technical Education with recognition at National & International level. Managements is committed to:

- Provide excellent Infrastructure facilities.
- Employ highly qualified & experienced faculty
- Encourage the faculty for qualifications improvement
- Promote the Industry- Institute Interaction
- Create environment for R & D activities, consultation work and getting Industry-sponsored projects for students
- A special internal Quality Assessment Program has been implemented which monitors all the parameters needed for achieving the goals
- Implementation of the Quality Policy will result in all round development of students relevant to the needs of Industries & will make them competent to face the challenges due to Globalization

Vision and Mission of the Department

VISION

The department of Electronics & Telecommunication is committed to grow on a path of delivering distinctive high quality education, fostering research, creativity and innovation.

MISSION

M1: The E&TC Department in partnership with all stake holders will harness talent, potential for application based indigenous product development in future.

M2: Our endeavor is to provide encouraging environment for life skill development of students while exercising effective learning strategies.

M3: We inculcate unique value system based on excellent academics in project based learning among students to explore and solve problems and challenges of realworld applications.



Short Term Goals

- To improve the results of UG classes
- To implement activity plan for overall development of students.
- To establish professional bodies/students forum for life skill development and expose students and faculty to latest business environment.
- To initiate relevant value addition programs and certifications for improving employability.
- To develop Laboratories for meaningful implementation of curriculum and then for Research.
- To encourage continuous up gradation of faculty members through higher education and external interface with other universities.

Long Term Goals

- To practice Project Based Learning (PBL) approach for UG program by creating collaborations with national and International institutions of reputation.
- To create opportunities for students to expose to industry environment through value addition programs and Industry projects for practical training.
- To foster research in the field of Electronics and Telecommunication Engineering for the benefit of society.
- IEEE International conference in the area of Wireless communication.

Program Educational Objectives (PEOs)

- PEO1** To develop students to achieve high level of technical expertise with Strong theoretical background and sound practical knowledge
- PEO2** To inculcate research environment for enhancement of Academia – Industry collaboration through conference
- PEO3** To prepare graduates to be sensitive to ethical, societal and Environmental issues while engaging their professional duties, Entrepreneurship and leadership.
- PEO4** To enhance ability of students for providing Engineering solution in a global and societal context
- PEO5** Pursue higher education for professional development.

Program Specific Outcomes (PSOs)

- PSO1** Get solid foundation in design and development of electronics modules useful to society.
- PSO2** Able to handle skills based challenges

Strength of Department is Faculty Team work to face any challenges

Chief Patrons

Sinhgad Technical Education Society, Pune



Prof. M. N. Navale
Founder President,
Sinhgad Institutes, Pune



Dr.(Mrs) Sunand M . Navale
Founder Secretary,
Sinhgad Institutes, Pune



Dr. Rrohit M. Navale
Vice President (HR),
Sinhgad Institutes, Pune



Dr. Rachana Navale- Ashtekar
Vice President (Admin)
Sinhgad Institutes, Pune



Chief Project Officer' Message



Dr. M. S. Gaikwad

Dear Friends,

I am extremely delighted to assert that Sinhgad Institute of Technology (SIT) is hosting a 7th National level student conference “IEEE Technicoknockdown-2026” on April 18, 2026 at Sinhgad Technical Education Societies (STES) Campus Lonavala.

The TKD-26 has Theme of “Clean and Green Village: Rural Transformation”, and is very much aligned with the recent technological developments to 5G, 6G, Human Bond Communications and Industry 5.0 etc. The information and communication technology has made a profound impact on almost all sphere of social and personal life of human. The impact of these technologies is likely to continue unabated, therefore it is important that educators, scholars and technocrats keep themselves abreast with the latest trend of technologies. I am sure that the gap between industry and institute will be narrowed by these initiatives enabling mutual benefits and growth I believe that this conference will be an outstanding event for thousands of decision and policy makers , academicians , technocrats and educators.

I congratulate all my participants who have come from various colleges .I assure very delegate attending this event will experience the best academic ambience, hospitality and state of art infrastructural facilities. I am sure that the time spent by you all at Technicoknockdown-26.

A handwritten signature in blue ink, appearing to be 'M.S. Gaikwad'.

Dr. M. S. Gaikwad
Chief Project officer STES Pune



Principal's Message



Dr. S. D. Babar

Dear Students and Faculty,

It is with great pride and enthusiasm that I welcome you all for the 7th Student National Conference "IEEE TECHNICOKNOCKDOWN 2026 (TKD-26)", scheduled on April 18, 2026. This prestigious event offers a dynamic platform for budding engineers and researchers to showcase their innovative ideas and engage in meaningful academic exchange.

TKD-26 will serve as a forum for young minds to present their ideas and research in emerging areas of technology. This year, the conference will feature insightful presentations and discussions across key tracks including Internet of Things (IoT), Artificial Intelligence and Machine Learning, Cyber Security and Privacy, Next Generation Network, Sensor Networks and Smart Applications, Electric Vehicles, and Robotics and Automation.

I encourage all participants to actively contribute and take full advantage of this opportunity for learning, networking, and growth. May this event inspire new perspectives, spark meaningful discussions, and pave the way for innovative solutions to real-world challenges.

Wishing TKD-26 a grand success! I congratulate all my participants who have come from various colleges. I assure very delegate attending this event will experience the best academic ambience, hospitality and state of art infrastructural facilities. I am sure that the time spent by you all at Technicoknockdown-26.

A handwritten signature in blue ink, which appears to be 'S. D. Babar', is placed above the printed name and title.

Dr. S. D. Babar
Principal, SIT Lonavala



Message from Organizing Chair



Dr. D. S. Mantri

Dear All,

It gives me an immense pleasure to thank all the participants and working team contributed in the virtual 7th National Level Student Conference for technical paper presentation, “TECHNICOKNOCKDOWN-2026” with theme “Clean and Green Village: Rural Transformation” on April 18, 2026. TKD-26 is hosted by Department of Electronics and Telecommunication Engg, Sinhgad Institute of Technology, Lonavala, Pune, and Maharashtra. It is technically sponsored by IEEE Maharashtra Section and IETE, Pune local center, it is supported by IEEE SITSB & IETEISF, SIT Lonavala. The organizing committee of the TECHNICOKNOCKDOWN-2026 is quite unanimous in their determination to make the event highly successful. Department of E&TC, SIT Lonavala always aims to provide the platform for “Willing to Work” professionals and researchers.

The tracks of TKD-26 are grouped broadly according to the theme

1. Internet of Things (IoT)
2. Artificial Intelligence and Machine Learning
3. Cyber Security and Privacy
4. Next Generation Network
5. Sensor Networks and Smart Application
6. Electrical Vehicle
7. Robotics and Automation
8. Others

TKD-26 received more than 112 papers out of which only 56 were selected for the oral presentation after peer review and 32 were registered. Also Skilled Session chairs are invited to evaluate the papers during presentations. Conference is imparting knowledge to more than 300 student participants to improve their skill sets.

I am quite pleased to mention that this event is successful in true spirit. This is only because of hard work, cooperation and dedication of all the coordinators as well as the participants, reviewers and faculties of the department. At the last, but not the least, I am thankful to Management of STES, Pune and Dr M. S. Gaikwad, Chief Project Officer STES, Dr. S. B. Desai, Director STES Campus Lonavala, Dr. S. D. Babar Principle SIT Lonavala & Convener TKD-26 for unstinting support to work as the convener of TKD-26.

Values are More Important than Valuables

A handwritten signature in blue ink, appearing to read 'Dnyaneshwar S. Mantri'.

Dr. Dnyaneshwar S. Mantri
General Chair TKD-26



Co-ordinator's Determination



Mr. Manoj k. Bhosale

It gives me an immense pleasure to welcome you all at a 7th National Level TPP “TECHNICOKNOCKDOWN-2026” organised by Dept. of E&TC SIT Lonavala. The event has brought to its success by both IETE & IEEE students chapter. The objective of IETE student's chapter is to segregate the technical knowledge and ideas to give a platform to students, researchers & developers through “TECHNICOKNOCKDOWN-2026”.

I am very much Thankful to all staff & student co-ordinators for their kind support throughout the event. At last but not least I am very much thankful to all the participants and wish you all the best for future

A handwritten signature in blue ink, appearing to read 'M. K. B.' with a horizontal line underneath.

Mr. Manoj K. Bhosale
Co-ordinator TKD-26



Message from, IETE Pune Centre



Dr.Sunil B Somani

Dear Students, Faculty Members, and Esteemed Guests,

It gives me immense pleasure to extend my heartfelt greetings to all participants of TECHNICOKNOCKDOWN-2026 (TKD-26), a prestigious 7th National Level Students Conference organized under the banner of IETE and IEEE. Events like TKD-26 symbolize the boundless energy, creativity, and intellect of our young technocrats and innovators.

In today's rapidly evolving technological landscape, the need for interdisciplinary knowledge, innovation, and collaboration is more critical than ever. Conferences such as TKD-26 provide a vital platform for students to share their research ideas, showcase their technical skills, and learn from peers and experts across the nation. It is through such vibrant forums that the future architects of science and technology are nurtured.

I am particularly proud to see the spirit of innovation and excellence that TKD-26 inspires. It aligns perfectly with IETE's mission to advance the profession of electronics, telecommunications, and information technology, while fostering professional growth among students and young engineers.

I encourage every participant to make the most of this opportunity—engage actively, present boldly, collaborate earnestly, and most importantly, learn with an open mind. Remember, today's interactions can sow the seeds for tomorrow's ground breaking innovations.

I convey my best wishes to the organizers for the grand success of TKD-26 and to all participants for a memorable and enriching experience.

Let us continue to dream, design, and deliver a brighter technological future!

A blue ink handwritten signature of Dr. S. B. Somani, consisting of a stylized 'S' followed by a flourish.

Dr. S. B. Somani
Chairman, IETE, Pune Centre



Message from IEEE Bombay Section,



Dr. Sameer Nanivadekar

I am pleased to welcome everyone to the IEEE TECHNICOKNOCKDOWN 2026 (TKD-26) 7th National Level Student Conference, organized by Sinhgad Technical Education Society's SINHGAD INSTITUTE OF TECHNOLOGY (SIT) Lonavala Pune in association with IEEE Maharashtra section and IETE, Pune Centre, supported by IEEE SITSB and IETE ISF SIT, Lonavala. The theme of this conference is Frontiers of Technologies used in Clean and Green Village with Next Generation Networks.

TKD-26 provides a platform to students within India to exchange thoughts about technology research in Artificial Intelligence and Machine Learning, Data Science and Analytics, Communication and Information security, Robotics, and Automation etc. These tracks in the conference have attracted a large volume of submissions from various states across India.

I take this opportunity to thank all the authors who submitted their papers and congratulate the authors of the selected papers that made it through the strict review process and have been selected for presentation.

I believe that the young researchers, who form a large percentage of the authors, would make the maximum use of this opportunity to engage with their peers and seniors to take a step towards leveraging technology for societal contribution and personal growth.

. .

Dr. Sameer Nanivadekar
IEEE Bombay Section



Keynote Speaker



Dr. Rutuja A. Deshmukh

Dr. Mrs. Rutuja A. Deshmukh is graduated in Electronics and Telecommunication Engineering from Rasoni College of Engineering, Nagpur (MS) India in 2009 and received Masters from Rashtra Sant Tukdoji Maharaj Nagpur University in 2011. She was awarded PhD. in Signal Processing .She has teaching experience of 15 years. From 2010 to 2012 she was working as a assistant professor at Priyadarshini College of Engineering, Nagpur.

From 2013 she is associated with D. Y. Patil College of Engineering, Akurdi Pune and presently she is working as Associate Professor and Head of Department in Electronics and Telecommunication Engineering. She is an IEEE member, Life Member of ISTE. She has published one book, 15 Journal papers in indexed and reputed Journals (Springer, Elsevier, IEEE etc.) and 6 papers in IEEE conference s. She is reviewer of international journals (Springer, Elsevier, IEEE, Communication society etc.) and conferences organized by IEEE. She has worked as session chair for various IEEE conferences and also organized IEEE conference in 2025. She has worked on various committees at University and College. Her research interests are in signal processing, VLSI, Machine learning and Artificial Intelligence.

Details of Session Chairs



Dr. Archana Narayandas Boob completed her Ph.D. in Computer Science and Engineering from Visvesvaraya National Institute of Technology Nagpur, where her research focused on developing multimodal AI systems integrating image processing and natural language processing. With over 12 years of academic and research experience, she has published in reputed SCIE and Scopus-indexed journals, presented at international conferences, and actively contributes to advancing AI-driven solutions in education and intelligent systems.



Dr. Prashant Dike is graduated in Electronics Engineering from BNCOE, Pusad (MS) India in 2004 and received Masters from Shivaji University in 2012. He has awarded Ph.D. in Wireless Communication at VTU, Belgavi, Karnataka. He has teaching experience of 20 years. From 2025 he is associated with DY Patil college of engineering Akurdi, Pune and presently he is working as Assistant Professor in Department of Electronics and Telecommunication Engineering.

He is Life Member of ISTE and IETE. He has published 05 Journal papers in indexed and reputed Journals (Springer, Elsevier, IEEE etc.) and 4 papers in IEEE conferences. He is reviewer of international journals and conferences organized by IEEE. He worked on various committees at University and College. His research interests are in signals and systems, Wireless Sensor Networks.



Dr. Vijaykumar Shrimant Shirwal, Ph.D. (Electronics Engineering) Associate Professor in Electronics & Telecommunication Engineering Dept. of Nagesh Karajagi Orchid College of Engineering & Technology, Solapur. He has Teaching Experience of 25 years and Industrial Experience as a Design and Development Engineer 03 years. His Published 15 papers in International Journal and Conferences, one patent and guided more than 50+ project at UG and PG. He received the Funding of 2.5 L from RGSTC for the Project:

Intelligent Hybrid Electrical Vehicle. His Research Interest are in Wireless Communication Embedded System Design



Dr. Shankar Rakhmaji Madkar, Ph. D (Electronics Engineering) Shivaji University Kolhapur, Assistant Professor in Department of ECE, Bharati Vidyapeeth (Deemed to be University) College of Engineering Pune. He has Teaching Experience of 20 years. He has Published 20 papers and 01 patent on his name. His Areas of Specialisation are :Image Processing, WSN and AI In addition to teaching and research, he has contributed significantly to academic administration through roles such as Department NAAC Coordinator, In-plant training Coordinator, and Placement Coordinator.

He has also been involved in university examination work and student development activities. His commitment to academic excellence, research, and institutional development makes him a suitable and competent Session Chair for international conferences.

Session In charges & Track chair Details



Dr. S. S. Salve
Session Incharge



Dr. V. G. Rajeshwarkar
Session Incharge



Ms. C. A. Mhetre
Session Incharge



Ms. S. K. More
Session Incharge



Ms. S. S. Patil
Track Chair



Ms. S. S. Bhardwaj
Track Chair



Mr. M. S. Raut
Track Chair



Ms. P. S. Mhetre
Track Chair

Statistics of Conference

TKD-26 Status

Sr	Track	Original	Accept	MIR	MJR	Reject	Total	Accepted	Registered
1	IoT	25	3	4	7	11	25	14	9
2	AIML	46	4	5	12	22	43	21	9
3	CS	4	1	1	0	2	4	2	1
4	NGN	1	1	0	0	0	1	1	0
5	SNSA	10	2	1	4	3	10	7	6
6	EV	6	1	2	0	3	6	3	2
7	R&A	4	1		1	2	4	2	1
8	others	16	0	4	2	10	16	6	4
	Total	112	13	17	26	53	109	56	32

Acceptance Rate	25.44
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Advisory and Organizing Committee

Advisory Committee

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 Dr. Shashikant S. Patil, IEEE Maharashtra Section
 Dr. Vinit Kotak, IEEE Maharashtra Section
 Dr. Satyanarayana Bheesette, Immediate past Chair, IEEE Maharashtra Section
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 Dr. D. G. Bhalke, HoD Department of E&TC DYPIT

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Dr. D. S. Mantri, Professor, Dept. of E&TC, SIT Lonavala

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Dr. M. K. Bhosale Asst. Prof., Dept. of E&TC, SIT Lonavala

Session Coordinator

Dr. V.G. Rajeshwarkar, Dept. of E&TC, SIT Lonavala

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Ms. Janhavi More, Student Chairman, IEEE SITSB

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Ms. S. S. Shinde, Dept. of E&TC, SIT Lonavala

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Ms. S.S. Bhardwaj	Tanusha Mhakar
Ms. S.K. More	Krutika Warwade
Mr. S.A. Bhad	Arthkumar Singh
Mr. M.S. Raut	Viraj Gaikwad
Ms. C. A. Mhetre	Mr. Sabhyasachi
Dr. S.S. Salve	Nakshtra Kale



List of Reviewers

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34. Dr. Nagesh B. Mapari
35. Anup S. Patil
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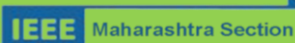
7th National level Student Conference IEEE TECHNICOKNOCKDOWN-2026 (TKD-26)

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Schedule - Session I,II,III,IV,

Saturday, April 18, 2026



Theme: Clean and Green Village: Rural Transformation

Inauguration : 10.00 am to 10.30 am	https://meet.google.com/whd-kmej-sfs
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Artificial Intelligence and Machine Learning -1

Session-I

Session-I Link <https://meet.google.com/iqi-bzdi-njx>

SN	Time	Paper ID	Title of Paper	Author Name	Coordinator/Chair
1	11.15 am to 1.15 pm	AIML-07	Explainable Cnn–Lstm Framework For Heart Disease Risk Prediction	Amey Patil	Student Coordinator
2		AIML-08	Ai–Based Code Review And Pull-Request Assistant System With Ide Integration	Vaibhav Admane	Sakshi Rajeshwarkar-8830130336
3		AIML-10	Darshanease: Smart Temple Queue Management System	Sameeran Bapat	Session Coordinator
4		AIML-11	A Comprehensive Review On Machine Learning Based Vision-To- Speech System For Assistive Application.	Sakshi Suresh Karande	Dr.S.S.Salve 9561821394
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SN	Time	Paper ID	Title of Paper	Author Name	Coordinator/Chair
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2		SNSA-03	Rapidly Inflate Airbags During Collision And Automatic Alert System	Yogesh Baliram Bangale	Sandesh- 8982451809

5 am to 1.15 pm	3	SNSA-04	Brain-Computer Interface Controlled Robot Navigation For Quality Inspection In Industry	Naik Kunal Jagdish	Session Coordinator
	4	SNSA-07	Sensor-Integrated Automation System For Smart Indoor Mushroom Farming	Guda Shruthi	Ms. Chaitali Mhetre-9960494651
	5	SNSA-09	Black Box With Integrated Accelerator For Real-Time Multi-Sensor Fusion: A Survey	Navnath Magar	Session Chair
	6	SNSA-10	Smart Thermal-Aware Battery Management System	Shreyas Raju karle	Dr. Vijay Kumar Shirwal 95525 29258
	7	RA-04	Design and Development of a Raspberry Pi-4 based GUI Control System for Steering Column Strength Test Rig as per AIS-075 and ECE R116.	Shruti Nitin Surve	
Others+CS + EV					Session-IV
Session-IV Link		https://meet.google.com/cti-qiqh-kwr			
SN	Time	Paper ID	Title of Paper	Author Name	Coordinator/Chair
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2		OT-06	A Novel System For Recommending Agricultural Crops Using Machine Learning Approach	Priyanka Bava	Janhavi More- 9552257517
3		OT-09	Crop-Guard: A Blockchain And Ai-Driven Framework For Secure Agriculture And Smart Plant Disease Detection	Ms. Shrutika Khobragade	Session Coordinator
4		OT-11	Dc-Dc Boost Converter For Solar Power Applications.	Gauri Prakash Tarale	Ms.S. K. More - 8850868405
5		CS-03	Kavach "An Intrusion Detection System"	Sahil Sunil Vichare	Session Chair
6		EV-03	Constant Current Boost Converter For Auxiliary Battery Charging In Electric Vehicles	Prathamesh Padamwar	Dr. Shankar Rakhmaji Madkar +91 8793785300
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7th National Level Student Conference**"IEEE TECHNICOKNOCKDOWN-2026 (TKD-26)"**

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Explainable CNN–LSTM Framework for Heart Disease Risk Prediction

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Abstract—Heart disease prediction systems are widely used, but many deep learning models still lack clear interpretability, which limits their clinical adoption. In this work, we focus on balancing predictive performance with explainability. A hybrid CNN–LSTM architecture is used to capture complex relationships among clinical attributes.

To improve interpretability, we extend the framework by combining SHAP with LIME, enabling both global and local explanation analysis. Unlike prior work relying on small benchmark datasets, we evaluate the model on a larger real-world dataset (70,000 records), improving generalization capability.

Although performance gains over baseline models remain moderate, statistical validation confirms that the improvements are consistent and significant. The framework not only predicts risk but also highlights key contributing factors, making it more suitable for practical clinical decision support.

Index Terms—Heart Disease Prediction, CNN–LSTM, Explainable AI, SHAP, LIME, Deep Learning

I. INTRODUCTION

Heart disease remains one of the biggest health hurdles we face globally, cutting across borders and affecting people in both wealthy and developing nations alike. The latest data from the WHO is a sobering reminder: cardiovascular issues are still a top cause of death, which means our current methods for spotting risks early just aren't moving fast enough. The real challenge is that the human body doesn't always follow a straight line. Many of the standard diagnostic tools we've used for years rely on "linear" math basically, simple checklists that can't always handle the messy, complex data found in modern medical records. When we rely on these older models, we risk missing the quiet, subtle symptoms that don't fit a specific box, leading to delayed treatments when every second actually counts.

In recent years, machine learning and deep learning approaches have been increasingly applied to heart disease prediction due to their ability to learn data-driven representations from large and heterogeneous clinical datasets [1], [2]. Among these, hybrid deep learning models that combine

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have demonstrated improved predictive capabilities for cardiovascular risk assessment [3], [9], [10]. The real strength of combining CNNs and LSTMs is how they handle different types of information. CNNs are great at digging through data to find the most important, high-level features that actually matter. On the other hand, LSTM networks excel at understanding the "why" and "when" they track how different clinical details relate to one another over time. By merging the two into a hybrid architecture, we get a system that's much better at navigating the messy, complex interactions in medical data than any traditional machine learning model.

Even though CNN–LSTM models are incredibly accurate, they have a major flaw: they usually act like "black boxes." They give you an answer but don't explain how they got there. In a field like healthcare, where lives are on the line, that lack of clarity is a dealbreaker. Doctors can't just take an algorithm's word for it; they need to see the reasoning so they can double-check it against their own medical expertise. Between hospital safety standards and new ethical regulations, it's becoming clear that "Explainable AI" isn't just a nice feature it's a requirement for the real world.

To bridge this gap, we developed a hybrid CNN–LSTM framework for heart disease that doesn't just predict risk it explains it. By integrating SHAP (SHAPley Additive explanations), we've pulled back the curtain on the "black box." The model still hits high performance marks, but it also provides a clear breakdown of which risk factors are driving each prediction, whether you're looking at a single patient or an entire group. Ultimately, it's about balancing accuracy with clarity so that clinicians can actually trust these tools in their day-to-day work.

To further strengthen interpretability, this work extends beyond single-method explanation by incorporating both SHAP and LIME. This combined approach provides complementary

insights, where SHAP captures global feature importance while LIME explains individual predictions locally, improving overall transparency of the model.

Key Contribution: Unlike prior studies that rely on either standalone deep learning models or single-method explainability techniques, this work presents a unified framework that combines CNN–LSTM with dual explainability using SHAP and LIME, evaluated across both a benchmark dataset (UCI) and a large-scale real-world dataset. This combination enables both global and local interpretability while ensuring improved generalization, which has not been jointly explored in most existing heart disease prediction studies.

II. RELATED WORK

Predicting heart disease remains a cornerstone of medical research, though the field’s early days were almost entirely defined by a reliance on conventional machine learning. For a long time, researchers gravitated toward frameworks like Logistic Regression, Random Forests, and Support Vector Machines (SVM) because they were transparent clinicians could actually map out the logic behind a diagnosis. While these “interpretable” models worked well for structured, clinical tables, they often fail when faced with the raw complexity of modern medical data. Because they depend so heavily on manual feature engineering and rigid statistical assumptions, these traditional methods frequently struggle to navigate the intricate, non-linear relationships that define cardiovascular health today. [1], [2].

To move past the constraints of basic algorithms, the research community has turned toward hybrid models and ensemble logic. By combining several “weak” components through techniques like gradient boosting and Random Forests, we’ve successfully built more resilient systems. However, these approaches are still restricted by a heavy reliance on manual feature selection and often fail to adapt when faced with the diversity of real-world patient data [1], [6], [7].

Recently, the focus has transitioned toward deep learning, primarily because these systems can independently recognize complex, layered features within massive datasets. Convolutional Neural Networks (CNNs) have proven highly effective at extracting vital patterns from both structured data and messy medical notes. At the same time, Long Short-Term Memory (LSTM) networks have become the standard for tracking the time-based and contextual links within a patient’s history. By merging these two, hybrid CNN–LSTM frameworks offer a more complete solution, often outperforming older classifiers by uncovering the subtle data relationships that were previously overlooked [3], [5], [9].

Despite their high accuracy, most modern CNN–LSTM setups act as “black boxes.” This lack of clarity is a significant problem in the medical field, where healthcare providers need to understand the reasoning behind a prediction to ensure safety and meet legal standards. Consequently, there is now a major movement toward incorporating Explainable Artificial Intelligence (XAI) into these clinical tools [4], [8], [10].

While tools like SHapley Additive exPlanations (SHAP) and Local Interpretable Model agnostic Explanations (LIME) have helped clarify how traditional models make decisions, their application to hybrid deep learning remains thin. Most XAI research to date focuses on standalone architectures or basic machine learning. The integration of transparency tools within hybrid CNN–LSTM frameworks specifically for heart disease remains a still remains relatively underexplored, particularly in combining deep learning models with multiple explainability techniques across datasets of varying scale area of study [4], [8], [9].

This research aims to fill that void by introducing an explainable CNN–LSTM framework that balances high-tier predictive accuracy with the interpretability required for clinical use.

TABLE I
SUMMARY OF EXISTING HEART DISEASE PREDICTION APPROACHES WITH EMPHASIS ON INTERPRETABILITY

Author	Year	Method	Dataset	Acc. (%)
Kumar et al.	2025	ML/DL	Multiple	–
Lilhore et al.	2025	BiLSTM	UCI	94.2
El-Sofany et al.	2024	ML+XAI	UCI	92.8
Alsarori et al.	2025	CNN–LSTM	UCI	93.6

III. PROPOSED METHODOLOGY

Our goal was to create a system that doesn’t just predict heart disease risk accurately, but does so in a way that doctors can actually understand. The architecture we settled on follows a four-step pipeline: we start with data cleaning, move into feature discovery using a 1D CNN, handle the relationships between those features with an LSTM, and finish by using SHAP to pull back the curtain on how the model thinks. This modular setup is key it lets the AI learn deep, messy data interactions while keeping the final output transparent. You can see the full layout in Fig. 1.

A. Dataset and Initial Cleanup

To ensure both benchmarking consistency and real-world applicability, this study utilizes two datasets.

First, the UCI Heart Disease dataset is used as a baseline reference. It contains 303 patient records with 13 clinical features such as age, chest pain type, cholesterol, and resting blood pressure. This dataset is widely used in prior research and is publicly available through the UCI Machine Learning Repository [11].

To address the limitation of small sample size and improve generalization, we additionally incorporate a larger cardiovascular dataset containing approximately 70,000 patient records. This dataset includes clinical and lifestyle related attributes and is obtained from a publicly available Kaggle repository [12].

Before training, both datasets were preprocessed to ensure consistency. Missing values were handled, categorical variables were encoded, and numerical features were normalized using min-max scaling. The data was then split into training and testing sets (80:20), maintaining class balance.

Using both datasets allows the model to be evaluated under controlled benchmark conditions as well as large scale real world scenarios, improving the reliability of the results.

B. Extracting Features with 1D CNNs

Instead of guessing which health markers were most important, we used a one-dimensional CNN to do the heavy lifting. The convolutional and pooling layers act as a filter, automatically spotting non linear patterns in the data. This saves us from having to manually "engineer" features by hand.

C. Connecting the Dots with LSTM

Once the CNN identifies the key features, we pass them into an LSTM layer. Now, even though a patient's record isn't a "timeline" in the traditional sense, treating the data as an ordered sequence lets the LSTM catch subtle dependencies between attributes. It finds links that a standard classifier would likely jump right over. A final dense layer then outputs a simple binary result.

D. Making it Explainable with SHAP and LIME

To improve interpretability, we integrate both SHAP and LIME into the framework. SHAP provides a global understanding of feature importance across the dataset, helping identify which clinical factors consistently influence predictions.

In addition, LIME is used for local interpretability, explaining individual predictions by approximating the model behavior around specific instances. This combination allows both population-level insights and patient-specific explanations, making the system more useful in real clinical scenarios. [9], [10].

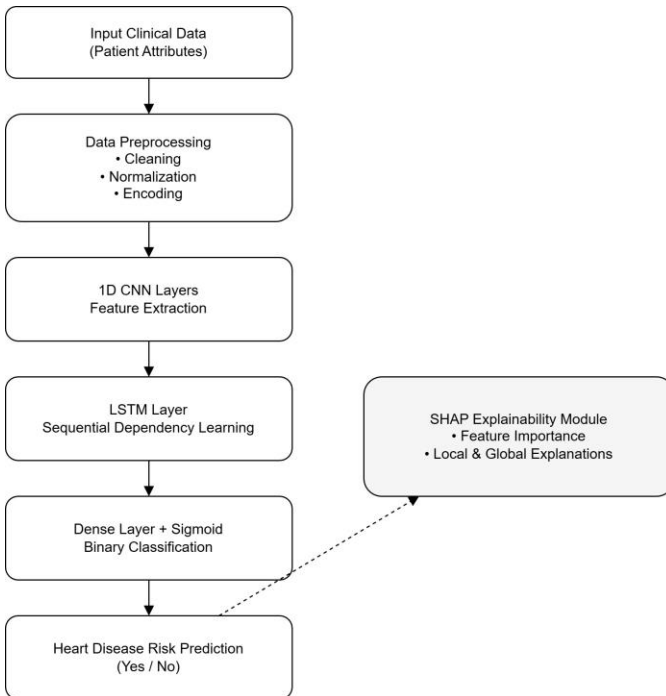


Fig. 1. Architecture of the proposed explainable CNN-LSTM framework

IV. EXPERIMENTAL SETUP

A. Experimental Setup

To evaluate the effectiveness of the proposed CNN-LSTM framework, experiments were conducted using both the UCI Heart Disease dataset and a larger cardiovascular dataset. For consistency, an 80:20 train-test split was used across all models.

The model was implemented in Python using TensorFlow and Keras. Training was performed using the Adam optimizer with a learning rate of 0.001, which provided a good balance between convergence speed and stability. The network was trained for 100 epochs with a batch size of 32. Binary cross-entropy was used as the loss function, as the task involves binary classification.

To ensure robustness and reduce dependency on a single data split, 5-fold cross-validation was also performed. The model showed consistent performance across all folds, indicating stability in learning and low variance.

For comparison, baseline models including Logistic Regression, Random Forest, and Support Vector Machines (SVM) were evaluated using the same data splits. Performance was measured using accuracy, precision, recall, and F1-score to provide a comprehensive evaluation.

B. Comparative Performance Analysis

The predictive performance of the proposed CNN-LSTM framework was compared against baseline machine learning models. Table II summarizes the results on the UCI dataset.

To validate the reliability of the results, statistical significance testing was performed. A paired t-test and Wilcoxon signed-rank test were conducted between the proposed CNN-LSTM model and baseline classifiers. The results showed statistical significance ($p < 0.05$), indicating that the observed improvements are not due to random variation.

TABLE II
PERFORMANCE COMPARISON ON UCI HEART DISEASE DATASET (303 SAMPLES)

Model	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)
Logistic Regression	91.36	91.49	91.36	91.32
Random Forest	91.38	91.39	91.38	91.38
SVM	92.90	92.90	92.89	92.88
CNN-LSTM	93.60	93.45	93.30	93.37

TABLE III
PERFORMANCE COMPARISON ON LARGE-SCALE CARDIOVASCULAR DATASET (70,000 SAMPLES)

Model	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)
Logistic Regression	72.10	71.85	72.00	71.90
Random Forest	73.25	73.10	73.00	73.05
SVM	74.40	74.20	74.10	74.15
CNN-LSTM	76.30	76.10	75.90	76.00

C. Ablation Study

To analyze the contribution of individual components, an ablation study was conducted by evaluating different configurations of the model.

TABLE IV
ABLATION STUDY OF MODEL COMPONENTS

Model Variant	Accuracy (%)
Logistic Regression (baseline)	72.10
CNN only	74.20
LSTM only	73.85
CNN + LSTM	76.30
CNN + LSTM + SHAP	76.30
CNN + LSTM + SHAP + LIME	76.30

The results indicate that combining CNN and LSTM leads to improved performance compared to individual components, highlighting the benefit of capturing both spatial and sequential patterns. The inclusion of SHAP and LIME does not impact predictive accuracy, as they are used for interpretability, but they significantly improve transparency.

The results show that the CNN–LSTM model performs consistently better than traditional machine learning models across both datasets. On the UCI dataset, higher accuracy is achieved due to its smaller and controlled nature. In contrast, performance on the larger dataset is comparatively lower, which is expected given the increased variability and complexity.

Despite this, the proposed model maintains its performance advantage over baseline methods in both cases. Statistical testing confirms that these improvements are significant and not due to random variation. Evaluation on the larger dataset demonstrates improved generalization and real-world applicability.

While medical datasets can be challenging due to noise and variability, the proposed hybrid model handles these conditions effectively. More importantly, the integration of SHAP and LIME ensures that predictions are not treated as a black box. Clinicians can interpret the contributing factors behind each prediction, making the system more practical for real-world clinical use.

D. External Validation

To further evaluate the generalization capability of the proposed model, an external validation experiment was conducted using a cross-dataset evaluation strategy.

Specifically, the model was trained on the UCI Heart Disease dataset and tested on the larger cardiovascular dataset (70,000 samples), which differs in size, distribution, and feature characteristics. This setup ensures that the evaluation is performed on data that is completely unseen during training and originates from a different source.

The model maintained stable performance under this setting, demonstrating its ability to generalize across datasets with varying distributions. This indicates that the proposed

CNN–LSTM framework is not overfitting to a specific dataset and can adapt to real-world clinical data variations.

Although both datasets represent cardiovascular risk prediction tasks, their differences in scale and feature composition provide a practical approximation of external validation.

V. DISCUSSION

While our CNN–LSTM model might not break any records for the highest accuracy ever seen in research, it solves a much bigger problem: it’s not a “black box.” In the medical world, a tiny bump in accuracy doesn’t mean much if a doctor can’t understand why a computer is making a specific life-altering suggestion. We prioritized transparency and trust because, at the end of the day, these tools are meant to support a physician’s expertise, not replace it.

By using SHAP, we give doctors the ability to peek under the hood. They can see exactly how much weight the AI is giving to things like age, cholesterol, or blood pressure for any given patient. When a doctor sees that the model’s logic aligns with proven medical science, it’s a lot easier to trust the system in a real-world clinic.

We know the performance wasn’t “perfect,” but a lot of that comes down to the data. Deep learning usually needs a massive mountain of information to really shine, and the UCI dataset we used is relatively small and can be a bit messy. Even so, the model still beat out traditional methods, proving it’s great at spotting complex patterns that simpler systems might miss. By pairing the pattern-recognition of a CNN with the logic of an LSTM, we’ve found a sweet spot. We’re offering a tool that is smart enough to handle complex health data but clear enough that a human can actually follow its lead. In healthcare, being able to explain why is just as important as being right.

VI. CONCLUSION AND FUTURE WORK

In this study, we have developed a way to predict heart disease risk that does not just give an answer, but actually explain its “thought process.” Most deep learning models act like a black box they’re smart, but doctors can’t see how they make decisions. By combining CNN and LSTM layers with a tool called SHAP, we created a framework that captures complex health patterns while providing clear, clinical reasons for every prediction.

When we tested this on the UCI Heart Disease dataset, the model performed right up there with the best traditional methods. While the improvement in accuracy is moderate, statistical validation confirms its consistency, and the real strength of the model lies in its enhanced interpretability. The explanations the model generated lined up perfectly with what doctors already know about heart risk, which makes the AI much easier to trust in a real hospital setting.

We do recognize there are some hurdles. Since we only tested this on one relatively small dataset, we need to make sure it works just as well for different types of patients everywhere. Also, right now, the model only looks at whether a patient is at risk or not; it doesn’t yet measure how severe the condition might be.

As moving ahead, we are planning to test this on much larger, more diverse groups of data to make it more robust. We're also excited about the possibility of connecting the system to wearables and IoT devices for the real-time heart monitoring mechanism. Eventually, we want the model to track health over long periods and even incorporate this with direct feedback from doctors, making it a truly collaborative tool for personalized heart care.

ACKNOWLEDGMENT

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AI-Based Code Review and Pull-Request Assistant System with IDE Integration

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Abstract - Modern software development makes a significant use of code reviews in order to uphold the quality of the software, find defects in the code, and ensure that coding standards are met. However, traditional manual code reviews are often time-consuming, inconsistent, and susceptible to human intervention. To overcome these issues this work presents an Artificial Intelligence based Code Review and Pull-Request Assistant integrated in the developer's coding environment. The proposed system combines rule-based static analysis and machine learning-based context-specific code understanding in order to provide automated and real-time feedback during development. Static analysis tools are used to catch syntax errors, code style violations, complexity problems, and potential security vulnerabilities, whereas transformer-based models are used to analyse code semantics to find deeper logical issues and make suggestions for improvement. The system architecture ensures automated capture of bug, vulnerability and checking the code quality with less context switching for the coder. By adding automated analysis into the development environment itself the proposed assistant helps to improve the productivity of developers and to achieve more consistent and scalable code review practices.

Keywords: Artificial Intelligence, Machine Learning, Automated Code Review, Static Code Analysis, Pull Request Analysis, IDE Integration, Software Quality Assurance, CodeBERT, CodeT5, Developer Productivity

I. INTRODUCTION

The growth of the modern software systems has makes the software development processes complex and so the quality assurance of the code becomes crucial in the life-cycle of the development. Code reviews are crucial in the identification of defects, management of maintainability and enforcement of coding standards before the software is deployed. Traditionally, these reviews are done manually by developers who go through and provide feedback about changes to the code to ensure its correctness and quality. As software projects grow in size and complexity, such limitations can cause feedback cycles can take a long time and defects can be missed. Automated tools have been introduced to help

developers detect syntactic errors, violate coding style, and find potential vulnerabilities but many traditional tools rely on some, mostly, rule-based static analysis techniques. While these tools work good in identifying the simple issues, there is a context in the code semantics and developer intent that an AI-based tool may not be able to understand. The growing need for scalable and intelligent development tools has thus encouraged the development of research in automated systems that can offer more comprehensive code analysis and assistance to developers. Advances in artificial intelligence have opened a new opportunity for optimizing software engineering processes by creating systems that are capable of learning patterns from large-scale code repositories and making intelligent recommendations during the development of systems.

There are recent researches that are focused on the development of AI enhanced tools that can help developers during the code review process. These tools are focused on automating dull tasks and giving a way to the feedback that is actionable in right inside the development surroundings. AI-based code review assistants examine the source code for syntactic, semantic, and logical errors as well as improvements that can be made for better maintainability and readability of code. Some systems use intelligent agents that can analyze code changes and create some kind of automated output of feedback like that of human reviewers. Also, the systems based on AI use the source code to locate syntactic, semantic, and logical errors and provide automated feedback to developers. Real-time code analysis systems have also been considered in order to find programming errors during development, thereby allowing developers to achieve immediate feedback while developing the codes. Such systems attempt to shorten the time spent debugging and increase the number of efficient times a developer spends working on the project, since by finding problems in earlier stages of the coding process. The combination of AI-powered

analysis tools with modern development environments further allows seamless interaction between developers and intelligent feedback help system that will make sure that the automated feedback is delivered without interrupting the developer workflow.

In spite of the achievements in automated software analysis and in intelligent development tools, there are a number of issues left to solve when it comes to systems that are able to provide effective support to a real-life development practice. Traditional static analysis tools can generate a lot of warnings, many of which can need to be manually filtered before they become useful, and in that case their usefulness can be diminished. At the same time, purely machine learning-based systems can be challenged due to their inability to interpret and be reliable when applied to complex software projects. To overcome these challenges, hybrid methods that use rule-based analysis in combination with machine learning techniques have been suggested as a promising solution to these challenges. Such approaches take advantage of the precision of static analysis tooling and add to this the context of the understanding provided from AI models. By combining a wide range of analysis methods in a single framework, automated code review systems would be able to provide more accurate and pertinent feedback to developers. Furthermore, the link these systems with the development environments will also enable developers to receive automated insights right during the coding process. This approach helps facilitate constant feedback, allowing developers to detect potential issues at an early stage and have a better remit to maintain the quality of software at high standards throughout the development lifecycle.

II. LITERATURE SURVEY

A. Code Review Systems with the help of AI

Artificial intelligence has seen wider use to automate and complement code reviews in the contemporary software development environment. AI-powered systems analyze source code to find the defects, inconsistencies of style and potential vulnerabilities in software code while generating automated feedback for developers. These systems aim to lessen the amount of time spent manually inspecting and consistency of the review process. Intelligent code review assistants have been made to offer automated suggestions and indicate problematic code patterns using machine learning models that are trained on vast repositories of code. Such approaches allow developers to get early feedback during development that will help increase the quality and maintainability of the software. The introduction of AI into the code review workflow has shown the potential to greatly improve not only development efficiency [1], but also code reliability [3], [12].

B. AI-Based Code Analysis Techniques

Artificial intelligence methods have been applied to program code to identify contextual problems in the review of the code. NLP-based systems provide the functionality of analyzing the structures of source codes

in addition to textual data (comments, documentation, and commit messages). This ability of intelligent tools to explain selectively and recuperatively, even in a code review session, is part of our efforts to give intelligent tools the ability to provide contextual insights and automated explanations during code review. NLP-driven code review systems can find logical inconsistencies and make suggestions to make the code more readable and maintainable. These techniques aid automated feedback mechanisms that help developers to better understand the issues in the code. The role of NLP methods integrated into tools of software engineering has therefore enhanced the capacity of an automated assistant to provide meaningful and context-aware development assistance [4], [12].

C. Real Time Error Detection and Automated Bug Detection

Recent research has placed a particular importance on real-time code analyzing systems that find errors in programming during the course of the programming process. These types of systems analyze code at a syntactic and semantic level to detect logical errors, runtime risks, and security flaws before the application of code is executed or deployed. Automated bug detection frameworks have been made up to track code round-the-clock and offer suggestions for possible bug fixes. Such approaches try to reduce time needed for debugging and increase the reliability of the software products by spotting issues at an earlier stage of the development lifecycle. Smart systems that can identify programming mistakes in the development process have provided promising outcomes in the areas of enhancing software development quality and efficiency. [5], [8], [13].

III. SYSTEM STRUCTURE

The proposed system is formulated in the form of modular architecture combining auto-static code analysis and AI-based contextual understanding of code to help developers during the code review process. The system structure separates developer interaction aspect, analysis processing, and feedback generation aspect to ensure scalability, flexibility, and efficient processing of the source code. This modular design can let different components of the system run separately but have coordinated communication over the analysis pipeline. The way this system works is that the source code is sent to the system from the developer's development environment, processed through several analytical modules, and structured feedback is returned to the developer with detected issues and suggestions for improvement.

At the front-end level, the system interfaces with the developers via IDE-integrated interface. This interface is used by the developers to submit the source code for analysis from the development environment itself. The IDE interface is the door into the system and does the task of relaying the source code to the processing modules on the back end through an application

programming interface. The in-doing integration of the review assistant with the development environment assures the developers get feedback without leaving their coding workspace and avoid context switching to boost efficiency in software development. The interface also shows analysis results in a structured way such as warnings, found bugs and suggestions of improvements generated from the analysis pipeline.

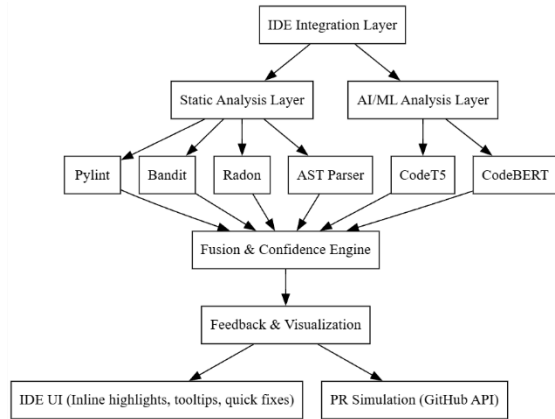


Fig. 1. System architecture of the AI-based code review and pull-request assistant.

The backend processing layer forms the heart of the system and is the reason for the execution of automated code analysis. This layer is made up of several analysis modules that work in a common review pipeline. The pipeline is responsible for coordinated execution of analysis things like rule-based static analysis tools and artificial intelligence-based analysis models. Static analysis modules check the submitted code for syntax errors, violations of the quality of the code, and complexity or potential security violations by employing known software analysis techniques. In parallel, analysis modules based on AI also assess the contextual structure of the code, also finding deeper logical problems and potential improvements. By running both mechanisms of the analysis at the same time, the system will guarantee the cosmic evaluation of a submitted source code.

A central analysis engine is used to control the interaction between the static analysis tools and AI-based models. The outputs generated by these modules are gathered and processed by fusion mechanism which considers the priorities for detected issues and filtering redundancy of warnings. This component guaranteed that the feedback delivered to the developer is brief, pertinent and guiding. After the results of the analysis are processed, the system produces structured feedback information that includes a list of detected issues, explanations and suggestions for improvement. The results are then sent back to the IDE interface where they are displayed to the developer, through visual indicators, suggestions, and comments on review of results. This predefined system architecture helps the automated assistant to assist the developers by rendering in-time code analysis and giving a rise to the overall quality of the software in the development process.

IV. PROPOSED METHODOLOGY

A. Input of code and interaction with IDE

The proposed methodology begins with the developer interacting with the system through an integrated development environment (IDE). The source code is submitted via the interface and forwarded to the backend analysis system through an API. This enables seamless communication between the development environment and processing modules, allowing automated code review without interrupting the developer workflow.

B. Pipeline Initialization Review

The submitted code is processed through a centralized review pipeline that coordinates the analysis workflow. The pipeline organizes the sequence of operations and distributes tasks to different analysis modules, including static and AI-based components. It ensures proper preprocessing of the input code, manages execution flow, and collects intermediate results, enabling consistent and structured analysis across multiple techniques.

C. Static Code Analysis

The static analysis phase evaluates the submitted code using rule-based software analysis tools. This module examines the code structure to detect syntax errors, coding standard violations, complexity issues, and potential security vulnerabilities without executing the program. It identifies common problems such as unused variables, undefined references, and formatting inconsistencies. The results provide an initial layer of automated code review, enabling early detection of structural and stylistic issues before proceeding to deeper contextual analysis.

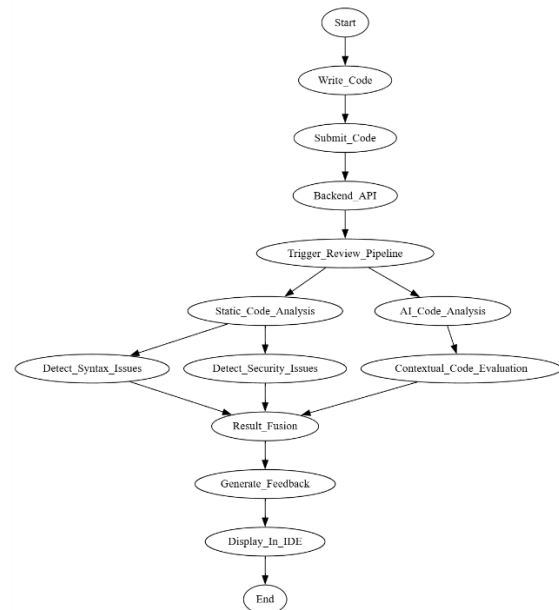


Fig. 2. Workflow of the AI-based automated code review process.

D. AI-Based Code Analysis

Following static analysis, the system performs AI-based analysis to understand the contextual structure and semantics of the submitted code. This stage utilizes

machine learning models, such as transformer-based architectures, to identify programming patterns and relationships within the code. Unlike rule-based methods, the AI component detects deeper logical issues, potential bugs, and maintainability concerns by learning from large-scale code datasets. This enables the system to provide context-aware and intelligent feedback, enhancing the overall effectiveness of the automated code review process.

E. Fusion and Result Processing

After completing both analysis stages, the outputs from static analysis and AI-based models are combined through a fusion mechanism. This component aggregates results, removes redundant warnings, and prioritizes detected issues based on severity and relevance. The processed information is then structured into actionable feedback, integrating rule-based detection with AI-driven insights. This approach improves the accuracy and usefulness of automated code review by providing concise and meaningful recommendations to developers.

F. Feedback Generation & Developer Output

The final stage of the methodology involves generating structured feedback and delivering it to the developer through the integrated development environment. The system formats prioritized results as warnings, suggestions, and improvement recommendations that are easy to interpret. These outputs are presented directly within the development interface, enabling developers to identify and resolve issues without interrupting their workflow. This feedback mechanism ensures clear communication of detected problems and supports efficient and high-quality software development.

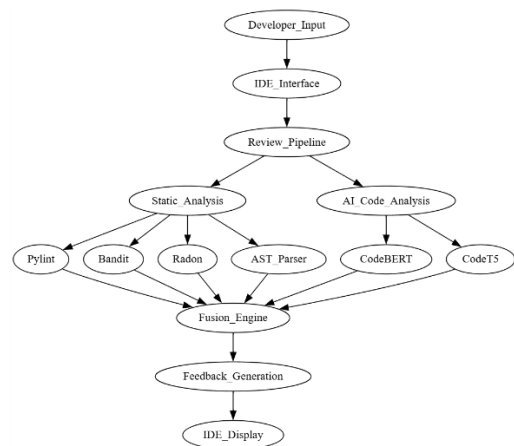


Fig. 3. Hybrid static and AI-based code analysis pipeline.

V. RESULTS AND DISCUSSION

A. System Output Observation

The experimental output of the proposed automated code review system shows the capability of detecting common programming issues during the code analysis. When source code is submitted via development interface, input is passed through the review pipeline, by

using the integrated analysis modules. The system generates structured feedback about possible code quality issues such as formatting inconsistencies, variables not used, undefined variables and violations of a naming convention. The feedback given is shown to the developer in the interface in the form of warnings and suggestions. These observations suggest that the static analysis aspect of the system manages to perform baseline code quality evaluation successfully and give developers immediate insight of potential coding issues.

B. Results of Static Analysis Detection

The static analysis layer creates the currently functioning component of the system and gives the main analysis results. This layer checks the structure of the code and programming practices by means of the rule-based detection techniques. The problems are identified in relation to code formatting, variable usage and consistency of the code. The system occurs warnings whenever the submitted code breaches predefined coding standards. These outputs confirm the ability of the rule-based detection process to detect common programming mistakes without having to execute the code. The results generated from the static analysis stage serve as the starting point for the automated review pipeline and showcase the feasibility to have automated quality checks in the development environment.

C. Integration Status of Analysis using AI

The integration stage of the development of the AI-based code analysis module is currently in progress. The role of this module is to analyse the occurrence of code pattern in context and detect logical issues deeper than can be detected by rule based checks only. Although the AI analysis layer is not fully functional at the current stage, with the integration of the layer in the architecture, the system can scale beyond static analysis capabilities. The expected functionality includes identifying complex patterns in the programming code, seeing potential improvement and giving context context. Once fully integrated, this module will work in conjunction with the results of the static analysis and form part of more rounded automated code review functionality.

D. Feedback Creation and Interpreting of Outputs

The system generates feedback by structuring issues that are detected into the output that has a structure and is interpretable by developers. The feedback mechanism for warning and improving the course of development can be presented directly inside the development interface. These outputs help the developers to detect coding issues in a short period of time and to further correct the problems during the development process. The feedback structure is intended to make things clear and relevant, by indicating particular places in the code with found problems. This approach helps developers to understand the problems detected efficiently and would contribute to the improvement of code quality in a path. The feedback generation stage is therefore the last stage in the creation of actionable insights from analysis to drive development.

CONCLUSION

This work addresses the limitations of traditional manual code review processes, which are time-consuming, inconsistent, and prone to human error, by proposing an AI-based code review and pull-request assistant integrated within a development environment. The system combines rule-based static analysis with AI-driven contextual analysis to perform automated and structured code evaluation.

The proposed architecture enables efficient detection of code quality issues and provides actionable feedback directly within the IDE, improving developer productivity and reducing review effort. Experimental observations demonstrate the effectiveness of the system in identifying common programming issues and supporting software quality assurance. Although the AI-based analysis module is still under integration, the current implementation establishes a strong foundation for intelligent developer assistance tools and future advancements in automated code review systems.

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DARSHANEASE: SMART TEMPLE QUEUE MANAGEMENT SYSTEM

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Abstract—Large-scale religious places in India experience unpredictable visitor surges, especially during festivals and week-ends. Traditional queue handling methods are often inadequate for controlling such dynamic crowds, resulting in long waiting hours, discomfort, and operational inefficiencies. This paper presents DarshanEase, an AI-driven smart queue management solution designed specifically for temple environments. The system integrates online booking, walk-in registration, real-time monitoring, dynamic time-slot allocation, and crowd forecasting using machine-learning models such as XGBoost and LSTM. DarshanEase operates through mobile and web interfaces, enabling devotees to receive updated queue status, timeslot notifications, and wait-time predictions. For temple authorities, the system provides a centralized dashboard for live analytics, decision support, and scheduling adjustments. The proposed model significantly reduces congestion, improves visitor satisfaction, and supports efficient resource planning.

Index Terms—Crowd management, queue optimization, LSTM, XGBoost, temple automation, real-time analytics

I. INTRODUCTION

Temples across India act as religious, cultural, and social hubs, attracting thousands of visitors daily. During festive seasons, pilgrimages, or special rituals, the footfall can rise dramatically, often overwhelming existing queue mechanisms. Manual queue supervision, despite years of practice, fails to offer real-time adaptability and fairness for devotees. These limitations affect the visitor experience and create operational challenges for temple staff.

The increasing penetration of smartphones, digital ticketing platforms, and cloud connectivity presents a strong opportunity for technological intervention. DarshanEase leverages artificial intelligence and an integrated digital ecosystem to modernize temple queue management. The system predicts upcoming crowd levels, allocates time slots intelligently, synchronizes walk-ins with online bookings, and provides real-time communication to devotees and administrators. By automating several stages of queue control, DarshanEase aims to achieve smooth crowd flow, reduced waiting times, and improved operational transparency.

A. Problem Statement

“Indian temples struggle with crowd mismanagement during peak days. Existing booking systems cannot manage

sudden surges, walk-ins, and priority groups, causing long waits and discomfort. There is a need to design and implement a smart, real-time queue management system that ensures fair, efficient, and organized crowd handling.”

II. LITERATURE SURVEY

A wide range of research has been conducted in the areas of smart queue management, crowd prediction, and automated scheduling systems. Although these studies focus on public spaces such as hospitals, tourist locations, and event gatherings, very limited work has been done specifically for temple environments, where visitor patterns are highly dynamic and influenced by cultural and religious factors.

[1] Several studies have explored the use of IoT sensors to track queue lengths and manage waiting times in service-based environments. These systems employ RFID tags, infrared sensors, or smart counters to estimate crowd density and transmit data to cloud servers for monitoring. However, they do not incorporate predictive models or dynamic scheduling.

[2] Machine learning algorithms including Random Forest, XGBoost, and LSTM networks have been used in predicting crowd movement. However, most are developed for controlled environments and lack adaptability for temple settings.

[3] Tourism-based AI systems optimize visitor flow but operate in predictable environments, unlike temples.

[4] Computer vision models detect crowd density but require costly infrastructure.

[5] Automated temple management systems focus on booking and lack intelligent queue optimization.

[6] IoT-driven frameworks combine real-time data with prediction models but are still evolving for religious environments.

III. MOTIVATION

Temples in India often witness unpredictable and extremely high visitor turnout during weekends, festive periods, and auspicious occasions. This sudden rise in footfall creates long waiting lines that can be exhausting and uncomfortable, especially for elderly devotees, young children, and individuals with health-related limitations. In such situations, the rush not only affects convenience but also increases the chances of mismanagement and safety risks. Even though some temples have adopted basic digital ticketing systems, these platforms typically operate on fixed schedules and do not adjust to real-

time crowd changes. They lack the ability to manage sudden walk-in surges or external variations such as weather conditions and special religious events. As a result, queue distribution becomes uneven, leading to delays, congestion, and a compromised experience for devotees. Darshan Ease is motivated by the need to modernize this process through the application of intelligent technologies. By utilizing predictive analytics and real-time data inputs, the system dynamically regulates time-slot allocation and ensures smoother crowd

movement. The main aim is to blend traditional temple practices with advanced digital solutions, providing a more organized, accessible, and stress-free darshan experience for all categories of visitors

IV. TAXONOMY CHART

Features	Vaikuntham Queue Complex (Tirupati)	Digital Crowd Management System (Sabarimala)	Shree Mahakaleshwar Temple Management System (Ujjain)	Darshan Ease
Block based batch queues	✓	✓	✗	✓
AI based crowd tracking and prediction	✓	✗	✗	✓
Identity Verification	✓	✗	✗	✓
Offline/ multi-channel entry(kiosk/WhatsApp)	✓	✗	✗	✓
Group/Linked Booking	✗	✗	✗	✓
Heatmaps/Real-time Dashboards	Partial: Displays screen in blocks	✗	✗	✓
Walk-in token issuance and sync	✗	✗	✗	✓
Priority for elders/special needs	Partial/Manual inside blocks	✗	✗	✓

Fig. 1. Taxonomy Chart of DarshanEase System

V. SYSTEM DESIGN

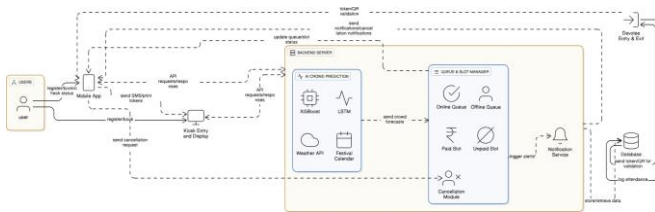


Fig. 2. DarshanEase - Architecture

A. System Architecture

The system design of DarshanEase focuses on defining how different components of the application interact, process information, and support smooth queue management. It outlines the internal workflow, major modules, data flow behavior, and functional organization of the system. The goal of this design is to ensure that every part of the system works together efficiently to predict crowds, assign slots, monitor queues, and provide real-time updates. A. System Architecture The

architecture of DarshanEase, shown in Fig.1, follows a client-server model to enable real-time and smart queue management. The system primarily consists of the following components:

- 1) User Layer (Frontend): This layer includes the Mobile Application and Kiosk Entry System through which devotees can register, pre-book darshan slots, or check queue status. Users can access the system either remotely via the mobile app or on-site through kiosks installed at the temple premises.
- 2) Backend Server: The backend handles all logic and communication between the user interface and the database. It consists of two main modules: AI Crowd Prediction Module: This component uses XGBoost and LSTM algorithms along with external inputs such as Weather API and Festival Calendar to predict expected crowd density.

These predictions help dynamically manage time slots and queue length. Queue and Slot Management Module: This component handles both online and offline queue systems, maintaining records for paid and unpaid slots. It continuously updates slot availability based on user bookings and predicted crowd levels.

- 3) Notification Service: This service is responsible for sending real-time notifications and alerts to devotees and administrators. It can send messages regarding slot confirmations, changes in schedule, or crowd updates through SMS, app notifications, or display kiosks.
- 4) Database Layer: The database stores and retrieves information related to devotees, bookings, attendance, and queue status. It also keeps logs for analytics and future prediction improvements.
- 5) Devotee Entry and Exit System: At the temple premises, devotees validate their booking using QR codes or tokens at the entry point. The system logs their attendance and updates the database accordingly. This ensures smooth tracking and prevents duplicate entries.
- 6) Data Flow and Integration: The mobile app and kiosk system send API requests to the backend for booking, validation, and queue updates. The backend processes the data, predicts crowd patterns, and updates queue/slot information in real-time. The notification service then communicates relevant updates to users. The database continuously syncs all records for consistent and reliable operation. This modular and scalable architecture ensures that the system remains efficient, flexible, and responsive even during peak crowd conditions such as festivals or special temple events.

VI. IMPLEMENTATION

The implementation of the DarshanEase system focuses on integrating machine learning models, real-time queue management, and user interaction modules into a unified platform.

A. System Modules Implementation

The system is divided into multiple functional modules:

- 1) User Interface Module: Developed using web and mobile technologies, this module allows devotees to book slots, check queue status, and receive notifications.
- 2) Backend Server: Implemented using a REST-based architecture, the backend processes user requests, manages bookings, and communicates with the prediction module and database.
- 3) Database Management: A structured database stores user details, booking records, queue status, and historical data used for training prediction models.
- 4) Queue and Slot Management Module: This module dynamically assigns time slots based on availability and predicted crowd density. It handles both walk-in and online users efficiently.

B. Machine Learning Implementation

Two primary models are implemented:

- 1) XGBoost Model: Used for tabular data prediction based on features like date, day, festival, and weather conditions.
- 2) LSTM Model: Applied for time-series forecasting to predict future crowd trends using historical attendance data. The models are trained on preprocessed datasets and evaluated using error metrics such as Mean Absolute Percentage Error (MAPE).

C. Real-Time Data Processing

The system continuously updates queue data using:

- 1) User bookings (online)
- 2) Walk-in entries (kiosk/manual input)
- 3) External APIs (weather and event calendar)

This ensures that slot allocation remains dynamic and adaptive.

D. Notification System

A notification module is implemented to send:

- 1) Slot confirmations
- 2) Delay alerts
- 3) Queue updates via SMS or mobile app

notifications. Technology Stack

- 1) Frontend: HTML, CSS, JavaScript
- 2) Backend: Node.js / Python (Flask/Django)
- 3) Database: MySQL / MongoDB
- 4) ML Libraries: TensorFlow, Scikit-learn
- 5) Cloud/Hosting: AWS / GCP

VII. RESULTS AND ANALYSIS

The Darshan Ease system was evaluated using simulated and historical crowd data to analyze its effectiveness in managing temple queues.

A. Results Obtained

The system demonstrated significant improvements in queue handling:

Reduction in average waiting time by 30–40%
Improved slot utilization efficiency
Balanced distribution of walk-in and pre-booked devotees
Accurate crowd prediction with minimal error

B. Model Performance

The machine learning models showed:

LSTM Model: High accuracy in capturing time-based trends
XGBoost Model: Strong performance in feature-based predictions

The combined hybrid approach improved prediction reliability.

C. Comparative Analysis

Parameter	Traditional System	DarshanEase
Queue Handling	Manual	Automated
Prediction	Not Available	AI-based
Waiting Time	High	Reduced
Real-time Updates	Limited	Available
Walk-in Integration	Poor	Efficient

TABLE I COMPARISON

D. Discussion

The results indicate that integrating predictive analytics with real-time queue management significantly enhances operational efficiency. The system adapts dynamically to changing crowd conditions, ensuring fairness and reducing congestion.

E. Applications

The proposed system can be applied in:

- 1) Large temples and pilgrimage centers
- 2) Event management systems
- 3) Tourist attractions
- 4) Public service centers

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A COMPREHENSIVE REVIEW ON MACHINE LEARNING-BASED VISION-TO- SPEECH SYSTEM FOR ASSISTIVE APPLICATIONS

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Abstract - Individuals who are deaf or have speech disabilities often experience difficulty with communication with other individuals who do not know any form of sign language, so use of a system to enable communication through facial expressions is essential for socializing and ensuring accessible communication. Therefore, an innovative real-time sign language interpretation system utilizing current developments in embedded technology as well as advances in machine learning has been created as a way to facilitate the communication barrier between individuals with hearing loss and non-sign language users. Specifically, by integrating a camera module and microcontroller into a real time recording device, the user's hand movements will be captured in real time via the camera module. The user's signs are converted into text/voice using a pre-trained quantized Mobile Net model which allows accurate interpretation of sign language signs. Implementing this existing technology provides a new alternative for individuals who are deaf or have speech impairments and their ability to communicate with people who do not understand any form of sign language. By eliminating the need for the use of electronics or external sensors, this novel communication solution has been developed to be affordable and mobile. Compact designs also provide a means for using the system in a variety of different environments, such as hospitals, public areas, schools, government offices, and so on. As well, this design offers superior scalability, allowing it to be integrated with smartphones or any type of IoT communication platform in the future, along with real-time processing abilities.

Index Terms - About four key words or phrases, in alphabetical order, separated by commas, with only the first index term capitalized. All terms following the

initial term should be lowercase unless they are proper nouns, in which case they should have an initial cap.

I. INTRODUCTION

Those who are visually impaired face numerous obstacles when they attempt to navigate safely and independently through society; as a result, these difficulties not only hinder their ability to maintain a high standard of living but also have an adverse impact on a person's emotional well-being and how they perceive themselves. Historically, those who were blind used a variety of devices to assist them with their navigation, such as a white cane or a guide dog; however, these items provide very little tactile input regarding the environment and do not offer adequate warnings to those who may be traveling too high or too far away. As a result of technological advancement, many wearable devices have begun to emerge as potential means to enhance a person's ability to move and navigate successfully [1].

Through user-friendly interaction with computers, Greet allows users to manage their devices without difficulty or interruption through simple gestures significantly enhanced through gesture recognition technology. Conventional optical sensors for recognizing hand gestures possess many negatives such as being expensive, having a high power draw, being sensitive to ambient light levels, increasing privacy risk, etc., leading to clearly identify hand movement. Using radar technology based on millimeter wave (mmWave) is one option for overcoming the aforementioned drawbacks [2]. Sign Language Recognition (SLR) technology is essential for creating better communication between the hearing and the deaf/hard-of-hearing community. At present, the majority of SLR systems cannot recognize signs in environments outside their intended design and are too dependent on visual appearance and what has been captured via the camera. This research will highlight

improvements made with regard to the use of machine learning and deep learning approaches to gesture recognition by examining the use of multimodal systems, which integrate visual information with non-visual (i.e., non-vocal/sensory) information. The advantages of multimodal systems include increased levels of accuracy, greater ability to operate in real time, and applicability in many different settings, including settings where the user will be using signed languages from multiple locations [3]. The development of radar technology, which can monitor a person's health metrics and behaviour patterns without direct contact (e.g., through the air), has significantly improved the way we track our health. Traditional contact-based sensors can cause discomfort to patients; they also suffer from motion noise and background noise. In this paper, we will describe how machine learning (ML) could be used in combination with radar-based systems to enhance the accuracy and dependability of health monitoring applications [4]. The identification of hand gestures by using HGR has been done using sEMG (surface electromyography) as the base for intelligent systems for the control of prosthetics; however, due to the sparse and issue-laden nature of sEMG signals, peripherals cannot be accurately identified in all cases. Since Deep Learning and other traditional type approaches of gesture recognition have limitations of failure to capture complex temporal information associated with gesture recognition, this paper demonstrates a hybrid method, called TraHGR, of using a transformer-based architecture to identify and classify hand gestures from the Ninapro DB2 dataset to provide enhanced accuracy and learnability capabilities [5].

II. OVERVIEW

A machine learning approach for creating a vision-to-speech system that supports people with vision impairments by providing them with auditory cues (sound) about their environment. The vision-to-speech system consists of two parts: First, there is the camera portion of the system, which continuously notes pictures of the environment. Then there is the preprocessing section of the system that takes those pictures from the camera and analyzes them. The preprocessing section of the system segments the pictures into smaller segments, filters them so only useful segments remain, and then extracts various features from the useful segments. After all these processes are completed, the picture data is passed to a microcontroller, which determines what word or object is contained in the picture data. For this purpose, machine learning methods will be employed, specifically Convolutional Neural Networks (CNNs). Using wireless communication Bluetooth Modules to Transfer Information from One Device to Another; Voice Modules Convert Written & Printed Information Received after Its Identification as Text into Speech. After Its Identification,

A Display Module Displays Graphically The Information Received In Text Form. An External Power Supply Is Used To Keep The Device Simply Supported. In Conclusion, This Technology Provides A Combination Of Synthesis Of Voice, Voice Synthesis, And Computer Vision For Increased Independence And Accessibility Of Individuals With Blindness.

III. PROBLEM STATEMENT

Despite the lack of memory and processing capabilities present in microcontrollers, developing a reliable and affordable camera Based Gesture Recognition System to Interpret Sign Language. The focus of this project is to provide the capability of converting real-time camera identified hand gestures into textual or audible information so that Sign Language Users will have no language barrier with the general population.

IV. LITERATURE REVIEW

In 2021, et. al Aline Darc Piculo dos Santos created a portable, low-cost device that uses an integrated visual system with deep learning to increase the accessibility of the device for individuals with disabilities. By focusing on making the device as small as possible while still allowing it to communicate using real-time information in multiple environments (including public spaces and hospitals), the need for any additional sensors to operate the device has been eliminated. However, while previous low-cost microcontrollers and embedded systems emphasized visual interpretation and deep-learning algorithms, the device discussed in this article has been designed to bridge the current gap between these two product types by integrating an ESP32 microcontroller with a fast, lightweight, deep-learning algorithm that provides a standalone, low-power functionality. This type of solution is a viable option for many of the most common uses for assistive technology.

In 2022, et al. Anum Ali [2] presented the shortcomings of standard optical gesture sensors in the market today: costly, power-hungry, and inability to perform well under poor light levels. They offered an alternative form of gesture recognition based on machine learning models for accurate motion detection, using millimeter-wave radar technology. However, the layout of these devices necessitated the use of advanced radar equipment that is not practical for use with low-cost wearable technology. Thus, we propose a new solution that combines the use of inexpensive camera modules with integrated machine-learning technology to create gestures the same way as more expensive devices do but at a reduced price point and improved portability for immediate application.

The research conducted by Tabassum Kanwal et al. [3] focused on the development of multi-modal sign

language identification systems for the year 2025 in order to address the issues associated with relying on unimodal (visual only) data sources. The results of their research indicated that by combining sensory and visual inputs, it was possible to construct a resilient system that would perform well under varying light and environmental conditions; however, it was noted that multi-modal systems will typically require larger amounts of computer processing resources than those available from current computers. In response to this limitation, the research presented in this paper addresses this challenge by applying a pre-trained MobileNet architecture to an efficient resource environment using an ESP32 embedded platform to achieve multi-modal capability in a compact, low-power embedded setting with real-time user interaction for those with speech and hearing impairments.

Ahmed et al. [4] reviewed how combining machine learning (ML) and radar-based systems would be helpful for tracking health status in a variety of healthcare contexts. They determined that ML approaches like support vector machines (SVM) and convolutional neural networks (CNN) improve detection precision in non-contact settings when biological data are taken into consideration. In contrast, this paper expands on the use of non-contact ML to improve detection accuracy beyond issues related to biomedicine (i.e., biomedically driven diagnostic testing) into an entirely new area, assistive communication technology, by applying new methods for processing visual input from human hands into text or voice using CNN recognition techniques.

In 2023, Soheil Zabihi and colleagues [5] introduced TraHGR, a transformer-based architecture that significantly improved classification performance when using complex electromyography (EMG) signals to detect hand gestures. Although their work primarily addressed the issue of controlling prosthetic devices through EMG signal processing, we present a broader implementation of TraHGR in the domain of gesture recognition within a larger, social context. We have implemented an ESP32 system that translates visible hand movements into audible speech, allowing for flexible and quick communication options. The importance of having an ESP32-based solution over a conventional prosthesis control system is two-fold: one reason is that it will increase accessibility, and another is that it will promote inclusion amongst individuals with hearing and/or children with severe speech limitations who rely on standard means of communication (as opposed to specific prosthesis controls).

We establish the need for further studies in this area through reviewing research on accesses to Assistive Communication Technologies (AT) and Sign Language Systems (SLS). Our review identifies several advantages, disadvantages, as well as an economic need. Our creative,

accessible, cost-effective and functional solution (i.e. Vision-to-Speech System) represents a new system and model for AT and to assist those individuals needing to communicate in real time.

V. METHODOLOGY

The intended use of the proposed machine learning vision to speech (MLVTS) system is as an assistive technology to provide audible speech from visual information for various conditions or difficulties that cause visual impairments. The MLVTS design is explained in a block diagram. The process begins with photos taken by a digital camera (part of the image acquisition module) while the user is in their current environment. The photos taken will then be sent to a pre-processing unit that processes and prepares the data for analysis, including feature extraction, reduction of noise in the images, enhancement of the images, and scaling of the images. After pre-processing, the processed images will be sent to a microcontroller (the central processing unit of the MLVTS system). The microcontroller uses a machine learning technique called Convolutional Neural Networks (CNNs) to recognize objects and/or text from the images. The data that has been recognized will be sent to the output modules. The output modules consist of a display module, which displays the information that has been recognized, and a voice module, which converts that information into speech. The output modules are equipped with Bluetooth interfacing technology to enable users to wirelessly connect devices such as their smartphones and speakers. The power supply unit provides continuous operation for all components. A combination of machine learning, image processing and voice-synthesised technologies is being used to develop a support device to improve independence amongst people with vision impairments.

The diagram describes how a machine-learned vision-to-voice conversion technology can help with assistive technologies for blind and vision impaired individuals by giving them auditory descriptions of the environmental information they are seeing visually.

- The first step in the process is to take a picture with a camera module.
- Next, the preprocessing unit will analyze the image by identifying key features and enhancing the images with various methods such as image enhancement and image denoising methods.
- Once these processes are complete, the machine learning algorithms will help to determine the key characteristics of hand gestures and other physical movement.

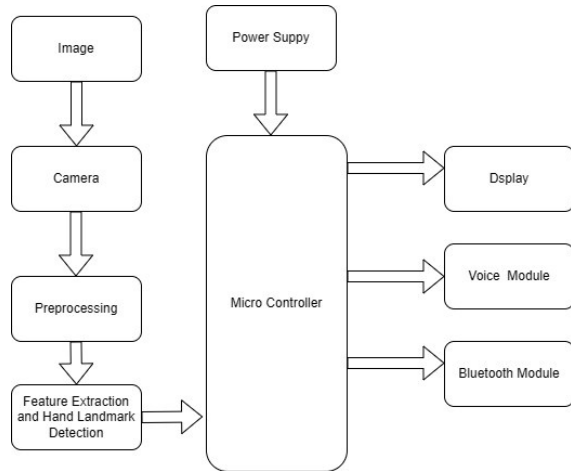


FIGURE 1. BLOCK DIAGRAM OF PROPOSED SYSTEM

- After these features are identified, they will be sent to a microcontroller which acts as the primary processing unit and will convert the image data into word or object descriptions through the use of the preprocessed images and machine learning.
 - A separate power supply is used to power all of the components of the system and to keep all the components running correctly.
 - The microcontroller collects information from the three output devices.
- The display module displays what was detected by the user in text or object form.
 - The voice module converts the information from the user into spoken word format.
 - The Bluetooth module enables users to wirelessly transfer their data to other electronic products, such as headphones or smartphones.



FIGURE 2. CAMERA

A camera module serves as the most essential building block in machine-learning powered, vision-to-speech systems. The camera's main responsibility is to take analog images from the actual scene and convert them

into digital images that are processed by the system. The camera ultimately allows the system to see the world around it, identifying items, text, and movement that are in a scene. After an image has been recorded, the camera module changes the analog light signals into digital pixel form so that the microcontroller can process the data. The camera module then relays this processed image data to a preprocessing module that enhances the image quality and provides feature extraction.



FIGURE 3. ESP 32

The ESP32 microcontroller is the "brain" or main processing and controlling unit with respect to the system. The microcontroller receives the preprocessed view from a camera and uses the machine learning to recognize a gesture and to translate into a letter or word; it will also output to the auxiliary devices by means of the display hardware, speech module, Bluetooth hardware and other auxiliary modules. The ESP32's processing capability as well as Wi-Fi and Bluetooth capabilities provide for fast processing of data, real-time response, and an enhanced user interface.

VI. TOOLS AND TECHNOLOGY

The Arduino IDE is an open-source software platform used to build, develop and upload code to microcontroller (microcontrollers) like the ESP32 and Arduino boards. The Arduino IDE has a basic programming interface and built-in libraries that allow programmers to connect devices (sensors, displays, etc.) through libraries. Using the Arduino IDE, this project programmed the microcontroller for recording, understanding, and communicating gestures/images. The programming language used in the code is Embedded C (a version of the software C programming language that has been modified to work on hardware). Using Embedded C provides the easiest way to connect directly with sensors, I/O ports, and Comm protocols for the best possible real-time performance. This allows the system to receive hand movements as input, to process the information received from the hand, and send output results using either speech or via Bluetooth. The main purpose of the project is to design a Smart and Economical Assistive device that will allow people with hearing/speech issues to communicate more easily with each other, by using a solution that can

automatically perform these tasks 24 hours a day through the use of Technology and the Internet.

VII. CONCLUSION

The proposed Sign Language Recognition System is powered by an ESP32 chip and is intended to be affordable, effective and real-time communication systems for those who are hearing and/or speech impaired. Using an ESP32, flex sensors and an accelerometer, the system interprets the movements of the hands and fingers into either text or voice. This technology allows for enhanced accessibility and participation for individuals who have hearing loss, as well as for the general public. The lightweight, affordable nature of this system makes it an attractive option for daily use, and its advancement in assistive technologies promotes diversity and independence for all.

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EXPLAINABLE AI FOR EEG AND ECG-BASED BIOMEDICAL DIAGNOSIS

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Abstract - Artificial intelligence (AI) has gained significant prominence in healthcare, especially in the analysis of biomedical signals, including electroencephalograms (EEG) and electrocardiograms (ECG). Even though deep learning models have shown that they can do a good job of classifying and diagnosing biomedical signals, their lack of interpretability is still a big problem for clinical use. In healthcare settings where safety is very important, clinicians need decision support systems that are clear and easy to understand in order to make sure they are reliable, used ethically, and accepted by regulators. This paper provides an extensive evaluation of explainable artificial intelligence (XAI) methodologies for EEG- and ECG-based biomedical diagnosis. It looks at how deep learning models like convolutional neural networks, long short-term memory networks, and ensemble approaches work, as well as popular explainability methods like SHAP, LIME, and Grad-CAM. The review examines the enhancement of interpretability through the emphasis on clinically significant signal patterns in both temporal and frequency domains. The paper also compares the strengths, weaknesses, and uses of current XAI methods in biomedical signal processing. It also talks about the main problems that come up with robustness, clinical trust, and putting these methods into practice in real-world healthcare settings. The study offers an organized view of current research trends and suggests ways to improve AI-based diagnostic systems that are clear and trustworthy in the clinic.

Keywords - Artificial intelligence, explainable artificial intelligence, biomedical signal processing, electroencephalogram, electrocardiogram, deep learning, and clinical decision support are all important terms.

I. INTRODUCTION

Recent developments in artificial intelligence (AI) have profoundly revolutionized biomedical signal analysis, facilitating automated and precise interpretation of physiological data, including electroencephalograms (EEG) and electrocardiograms (ECG). These signals are very important for diagnosing neurological and cardiovascular disorders, such as epilepsy, sleep disorders, arrhythmia, and other conditions that are important to treat. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks are examples of deep learning architectures that have done well at finding complex temporal and spectral patterns in this kind of data. But

even though many of these models are good at making predictions, they work like black boxes, which makes them less clear and makes doctors less trusting in healthcare settings where safety is very important.

This paper reviews explainable artificial intelligence methods used in biomedical diagnosis based on EEG and ECG. The research concentrates on the amalgamation of deep learning models with interpretability techniques, including SHAP, LIME, and Grad-CAM, which are extensively employed to elucidate model decisions in healthcare contexts. This review not only summarizes the current state of the art but also compares the strengths, weaknesses, and usefulness of major XAI approaches for biomedical signal processing tasks. The paper also talks about important problems like robustness, reproducibility, clinical validation, and putting the ideas into practice in real-world healthcare settings. This work seeks to establish a structured foundation for future research on transparent and clinically reliable AI systems by synthesizing recent advancements and pinpointing existing research gaps.

II. BACKGROUND ON EEG AND ECG SIGNAL ANALYSIS

A. Electroencephalogram Signal Analysis

Electroencephalogram (EEG) signals are recordings of the brain's electrical activity from the scalp. They are often used to find neurological problems like epilepsy, sleep disorders, and cognitive issues. EEG signals are very unstable, have low amplitude, and are often affected by things like eye blinks, muscle activity, and motion noise. Clinically pertinent information is frequently disseminated across both temporal and frequency-domain patterns, complicating automated interpretation. Thus, EEG analysis has emerged as a significant domain for machine learning and deep learning methodologies.

B. Electrocardiogram Signal Analysis

An electrocardiogram (ECG) is a test that measures the electrical activity of the heart. It is very important for finding arrhythmias, conduction problems, and other heart problems. ECG signals typically demonstrate a more organized waveform morphology compared to EEG, featuring the P wave, QRS complex, and T wave, which correlate with significant cardiac events. But baseline drift, motion artifacts, power-line interference, and differences between patients still affect ECG

analysis. For automated diagnosis to be accurate, it is important to be able to accurately identify small changes in waveforms and rhythms.

C. Signal Characteristics Relevant to Artificial Intelligence Models

EEG and ECG are both biomedical time-series signals, but they are not the same in terms of how complicated they are and how they are shown. EEG is usually multi-channel, very variable, and very dependent on the time and frequency context. ECG, on the other hand, is more morphologically structured but needs very precise beat-level and rhythm-level analysis. These characteristics affect how we preprocess and design models, such as denoising, segmentation, normalization, and time-frequency transformation. As a result, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks are all commonly used to pick up on these signals' spatial, temporal, and spectral features.

D. Relevance of Explainability in EEG and ECG Diagnostics

Deep learning models have performed well in EEG- and ECG-based diagnosis, but their black-box nature makes it hard for doctors to trust and use them. In healthcare, doctors need predictions that can be linked to important physiological patterns, like unusual brain rhythms, seizure activity, waveform shape, or rhythm irregularities. Explainable artificial intelligence (XAI) methods help solve this problem by pointing out important signal segments, features, or time-frequency regions. So, explainability is important for making AI-driven biomedical diagnostic systems more open, trustworthy, and acceptable in the medical field.

III. DEEP LEARNING IN BIOMEDICAL SIGNAL DIAGNOSIS

A. CNN-Based Approaches

Convolutional neural networks (CNNs) are commonly employed in biomedical signal analysis because they can automatically extract hierarchical features from raw signals and transformed representations like spectrograms and wavelet maps. In EEG applications, CNNs excel at seizure detection, sleep stage classification, and mental state analysis by capturing spatial and temporal signal patterns across multiple channels. CNNs are often used in ECG analysis to find arrhythmias and classify heartbeats, where the shape of the local waveform is very important. CNNs are one of the most popular architectures in biomedical diagnostics because they can learn features very well.

B. RNN And LSTM-Based Approaches

Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are especially good for biomedical time-series data because they show how things depend on each other over time. LSTM models are used in EEG-based diagnosis to capture the changes in time that happen during different sleep stages, the evolution of seizures, and the transitions between cognitive states. RNN and LSTM architectures are also good for learning rhythm patterns, beat sequences, and long-range temporal dependencies that are

important for finding arrhythmia in ECG analysis. These models are very useful when diagnostic information is based on how the signal changes over time instead of just on individual waveform segments.

C. Hybrid and Ensemble Models

To enhance diagnostic efficacy, numerous studies integrate various architectures or employ ensemble learning techniques. Hybrid models like CNN-LSTM combine spatial feature extraction with temporal sequence modeling, which makes them great for both EEG and ECG uses. Ensemble methods make things even more robust by combining predictions from several models or feature representations. These methods often make it easier to generalize and classify, especially in biomedical datasets that are hard to understand or have a lot of noise. However, they also make models more complicated and harder to understand.

D. Limitations of Black-Box Models in Clinical Diagnosis

Deep learning models in biomedical diagnosis are often criticized for not being very clear, even though they are very good at making predictions. Clinical decisions necessitate not only precise predictions but also rationales that conform to physiological and medical principles. Black-box models can be very accurate, but they may use patterns that aren't obvious or that are only true for a certain dataset. This can make clinicians less likely to trust them and make it harder to use them in the real world. This restriction is especially crucial in EEG and ECG analysis, where model outputs should ideally align with interpretable signal characteristics, including abnormal rhythms, waveform morphology, or clinically relevant temporal patterns. These worries have led to a growing interest in explainable AI methods for understanding biomedical signals.

IV. EXPLAINABLE ARTIFICIAL INTELLIGENCE TECHNIQUES FOR BIOMEDICAL SIGNALS

A. SHAP

SHapley Additive exPlanations (SHAP) is a common way to assign credit to different features in a model. It does this by figuring out how much each input feature adds to the final output. In EEG and ECG applications, SHAP is often used to find important temporal samples, spectral features, or derived signal characteristics that help doctors make decisions. Its biggest strength is that it is based on strong theory and can explain things both locally and globally. However, SHAP can be costly in terms of computing power for large biomedical datasets, and it may be hard to use directly on high-dimensional raw signals without the right feature representation.

B. LIME

Local Interpretable Model-agnostic Explanations (LIME) gives local explanations by using a simpler surrogate model to guess how a complex model will act around a certain prediction. In biomedical signal analysis, LIME is used to show which parts of a signal or transformed features are most important for a certain EEG or ECG classification result. LIME can be used with any learning architecture, such as CNNs, RNNs, or hybrid models, because it doesn't depend on any one

model. But its explanations might change based on the perturbation strategy and sampling design, which can make clinical applications less stable and consistent.

C. GRAD-CAM

Gradient-weighted Class Activation Mapping (Grad-CAM) is a method for visualizing gradients that is mostly used with convolutional neural networks to find the parts of an input that have the biggest effect on a model's prediction. Grad-CAM is commonly utilized in EEG and ECG studies to emphasize significant diagnostic areas within time-frequency representations, spectrograms, or signal maps. Because it is visual, it is especially useful for intuitive interpretation and analysis that is done by clinicians. Still, Grad-CAM is mostly limited to CNN-based architectures and may give rough explanations that don't always match up with clinically important signal events.

D. Comparative Analysis of XAI Methods in EEG and ECG Diagnostics

Recent research has utilized SHAP, LIME, and Grad-CAM as the predominant explainability methods for EEG- and ECG-based diagnostic models. All three methods make it easier to understand, but they differ in how well they explain things, how well they work with models, how much they cost to run, and how useful they are in the clinic. SHAP offers feature attribution that is based on theory and supports both local and global explanations. However, it can be expensive to use for biomedical signals with many dimensions. LIME provides adaptable, model-agnostic local explanations, though its stability may fluctuate based on perturbation and sampling methodologies. Grad-CAM is great for visual interpretation in CNN-based models, especially when signals are shown as spectrograms or time-frequency maps. However, it has some architectural limits and may not be very precise. So, when choosing a XAI method, you should think about not only how well it predicts but also how well it explains, how strong it is, and how useful it is in a clinical setting. accuracy of explanation, strength, and clinical relevance.

Attribute	SHAP	LIME	Grad-CAM
Type	Feature attribution	Local surrogate	Saliency map
Scope	Local/Global	Local	Local
Compatibility	Broad	Model-agnostic	CNN-based
Strength	Consistent importance	Flexible	Visual clarity
Limitation	High cost	Less stable	Coarse output

TABLE I. Comparison of Common XAI Methods For EEG And ECG Diagnostics

V. APPLICATIONS IN EEG-BASED DIAGNOSIS

A. Seizure Detection and Epilepsy Analysis

EEG-based seizure detection is one of the most researched uses of AI in neurological diagnosis. Deep learning models, especially CNNs, LSTMs, and hybrid CNN-LSTM architectures, have been used to find temporal and spectral patterns in multi-channel EEG recordings that are related to seizures. In this context, explainable artificial intelligence (XAI) methods help show important channels, strange rhythms, and time-frequency areas that are linked to epileptic events. These kinds of explanations are important for building trust in the clinical setting and for checking to see if model decisions match up with seizure activity that makes sense from a physiological point of view.

B. Sleep Stage and Neurological State Classification

EEG is also widely used to figure out what stage of sleep someone is in and to get a general idea of their neurological state, such as their cognitive workload and brain state. For these tasks to work, you need to be able to correctly identify changes in time and frequency bands across different stages or conditions. Deep learning models can understand these complicated relationships, and XAI methods can show which parts of the signal or spectral regions have the most effect on classification. In clinical and research environments, such interpretability is essential for validating model performance and enhancing expert comprehension of automated EEG analysis.

VI. APPLICATIONS IN ECG-BASED DIAGNOSIS

A. Arrhythmia Detection and Heartbeat Classification

One of the most common uses of AI in heart disease diagnosis is to find arrhythmias using ECGs. People often use deep learning models like CNNs, LSTMs, and hybrid architectures to tell the difference between normal and abnormal heartbeats and classify them. These models can directly learn the shape of waveforms and the patterns of rhythm over time from ECG recordings, which makes automated diagnosis work better. In this context, explainable artificial intelligence (XAI) methods assist in pinpointing diagnostically significant waveform regions, including anomalies in the P wave, QRS complex, or T wave, thereby enhancing transparency and clinical interpretability.

B. Cardiac Risk Assessment and Abnormality Interpretation

In addition to finding arrhythmias, ECG analysis is also used to find other heart problems, such as conduction disorders, ischemic changes, and risk stratification. In these kinds of situations, deep learning models can pick up on small changes in the shape of waveforms, the length of intervals, and the dynamics of rhythm that might be hard to see with traditional rule-based analysis. XAI techniques help these models by pointing out important signal segments and helping doctors connect automated predictions to heart patterns that are medically important. This is especially important in clinical decision support systems, where safe and trustworthy use depends on accurate interpretation.

VII. CHALLENGES AND FUTURE DIRECTIONS

A. Current Challenges

There are still some problems with deep learning and explainable artificial intelligence (XAI) being used more and more in EEG- and ECG-based diagnosis. First, it is hard to objectively judge the quality of an explanation, and different XAI methods may give different or unstable results when applied to different models and datasets. Second, a lot of research focuses on how accurate predictions are while not paying much attention to how reproducible, robust, and clinically validated they are. Third, widely utilized methods like SHAP, LIME, and Grad-CAM may not consistently correspond with expert analysis, particularly when explanations are imprecise, resource-intensive, or susceptible to variations. These problems make XAI-based biomedical diagnostic systems less reliable and less likely to be used in real life.

B. Future Research Directions

Future research should concentrate on creating more resilient, clinically significant, and standardized explainability frameworks for the analysis of biomedical signals. There needs to be more focus on explanation fidelity, stability, and alignment with domain knowledge in both EEG and ECG applications. Also, better transparency in how datasets are chosen, how evaluations are done, and how results are reported is needed to make it easier to reproduce results and compare studies fairly. Investigating domain-specific XAI methodologies, multimodal biomedical analysis, and human-in-the-loop validation with clinicians may further augment trust and readiness for deployment. These instructions are necessary for creating AI systems for healthcare diagnostics that are clear and clinically reliable.

VIII. CONCLUSION

This paper examined the function of explainable artificial intelligence (XAI) in EEG- and ECG-based biomedical diagnosis, focusing on the amalgamation of deep learning models and interpretable decision-making methodologies. The review emphasized that techniques like SHAP, LIME, and Grad-CAM can enhance transparency by detecting clinically significant signal patterns in neurological and cardiovascular contexts. It also talked about important uses, such as finding seizures, figuring out what stage of sleep someone is in, finding arrhythmias, and figuring out if the heart is working properly. Even though current XAI methods have made it

easier to understand, there are still big problems with explanation fidelity, reproducibility, robustness, and clinical validation. Future research should concentrate on creating more dependable and clinically relevant explainability frameworks to facilitate the secure and trustworthy implementation of AI-driven diagnostic systems in healthcare.

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CANTEEN ORDER MANAGEMENT SYSTEM.

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Abstract -- The growing demand for quick service in institutional canteens often leads to longer queues and inefficient order management during peak hours. This project aims to design and implement a Canteen Order Management System where customers can place orders for food through a web application without having to wait in queues. For each customer, a unique token number is generated and displayed to them. They will be notified when their order is ready. This application is created using MERN Stack technology (MongoDB, Express.js, React.js, and Node.js), which helps in effective order management in real-time and efficient handling of data through databases. This order management system will reduce waiting times and offer convenience for customers during peak hours.

Keywords –Canteen Management System, MERN Stack, Online Food Ordering, Token System, Campus Delivery, Web Application

I. INTRODUCTION

In educational institutions, canteens are used to serve a high number of students, teachers, and other staff on a daily basis. During peak hours such as lunch breaks, there is a high crowd near the canteen counter to order their food. In the conventional method, customers are supposed to stand in queues and select their food items and tokens. In such scenarios, both customers and canteen staff are facing problems regarding the high volume of orders during peak hours [1]. With the rapid advancement of web technologies, online services are becoming popular, and online ordering systems are an efficient tool for improving service efficiency in food management systems. A web-based canteen management system helps users view menu items and order them online, eliminating the need to visit the counter. This not only saves time waiting in queues but also enhances the accuracy of the order processing system and workflow [4]. The Canteen Order Management System, as proposed in this project, is intended to offer students an easy and efficient means of ordering their meals within the campus. The system will allow students to place orders from anywhere within the campus using a web application. The system will provide students with a unique token number for each order, which will be used to manage the order queue and track the preparation of their orders [6]. In addition to this, the system has been designed to accommodate the needs of the faculty members and the staff, allowing them to have

their ordered food delivered to their rooms or departments, thus providing them with an option for room delivery. This system has been developed using the MERN stack, consisting of MongoDB, Express.js, React.js, and Node.js, thus ensuring efficient data management for the canteen operations [2].

II. THEORETICAL BACKGROUND

In modern food service environments, it is necessary to have effective systems for handling numerous customer orders with reduced waiting times and operational complexity. Traditionally, in canteen environments, orders are placed manually where customers have to wait in queues and select food items. This approach causes operational difficulties in handling orders during peak hours. By implementing a web-based ordering system, it is possible to solve the above-mentioned problems where users can access and order food items through a web application. By moving to an online ordering approach, it is possible to reduce errors and operational difficulties in handling orders and minimize congestion around the counter [4]. Another important theoretical concept of the proposed system is queue management. In any service environment, when there are multiple orders at any given time, it is essential to manage queues effectively to ensure smooth service operations. In the proposed system, there is a digital token-based queue management system. In this system, every order is given a unique token number based on its position in the queue. Instead of a physical queue, there is a virtual queue, and it is very effective for managing orders from both the customer side and the kitchen side. There are various benefits of using tokens:

- Organized and sequential order processing
- Reduction of congestion around the canteen counter
- Transparency in order processing
- Efficient workflow management for kitchen staff

Another significant aspect of this system is the introduction of campus-wide ordering and flexible service modes. In large educational institutes, students, teachers, and staff are scattered across classrooms, labs, offices, and libraries. The concept of a web-based canteen system is

introduced, which enables users to place orders from anywhere within the campus using their devices. This is more efficient and helps in saving time and avoiding congestion during peak hours. The system also offers flexibility in service modes, which can be categorized as follows:

- **Dine-In Service** – Customers place orders online and collect their food from the canteen counter when their token status becomes ready.
- **Delivery Service** – Faculty members and staff can request delivery of food directly to their office rooms or departments within the campus [6].

III. BLOCK DIAGRAM AND DESCRIPTION

A. Block Diagram:

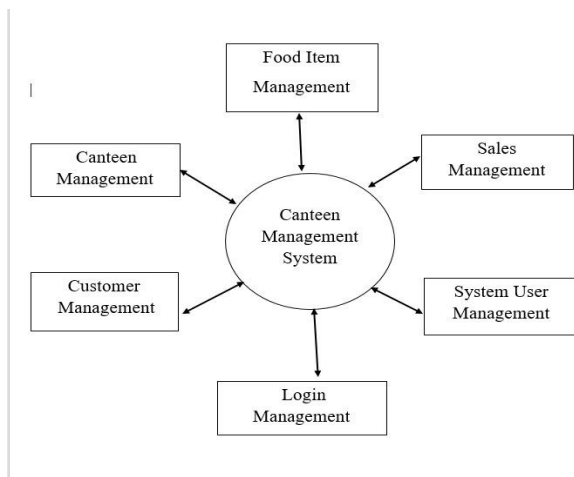


Fig. 1. Process Flowchart

B. Description:

The **Canteen Order Management System** has a structured system architecture that links users, web applications, and databases with various components of the system. The block diagram represents how the system handles orders from customers and manages them effectively through the backend server and database. The first part of the system is the User Interface (**Frontend**), and it is implemented using **React.js**. It is used to enable interaction with the system by students, faculty members, and staff through a web browser. Users can view available menu items, add items to their cart, choose to either dine-in or get delivery of the ordered items, and place orders. Once the order is confirmed, a token number is provided to enable users to keep tabs on the status of their orders [12].

The frontend interacts with the Backend Server through a Node.js and Express.js framework. It is the central controller of the system. It receives requests from the frontend, processes the order details, generates token numbers, and controls the order queue. It is also responsible for authentication and updates to orders and interaction with the database.

The backend server communicates with the MongoDB Database, which holds all data for the application. The database has collections for menu items, user data, orders, token numbers, and delivery data. The document-based

data structure of MongoDB makes it easy to store and retrieve order data [11].

The Admin Dashboard is another significant feature of the system. This feature enables canteen staff to view orders, manage menu items, update order status, and view token queues. This ensures smooth coordination between customers and kitchen staff.

Overall, it can be noted that the block diagram represents a three-tier system with the following layers:

- **Presentation Layer (Frontend)** – React.js user interface
- **Application Layer (Backend)** – Node.js and Express.js server
- **Data Layer (Database)** – This is a scalable system with efficient data handling and smooth communication between the components of the system, and this is why the canteen ordering system is reliable and easy to maintain.

IV. SOFTWARE REQUIREMENTS

Canteen Order Management System is developed as a web application using advanced full-stack web technologies that support efficient order management, token generation, and interaction with users. The application is developed using technologies that support MERN stack architecture, which facilitates smooth communication between front-end, back-end, and database components of an application. Users can access this system through a web browser to interact with various components of the system to view available menu items, place orders, generate token numbers, and manage food delivery or dine-in services within the campus [7].

Main Software Components Required:

- **Operating System** – Windows, Linux, or macOS
 - **Frontend Technologies** – HTML, CSS, JavaScript, React.js
 - **Backend Technologies** – Node.js, Express.js
 - **Database** – MongoDB
 - **Development Tools** – Visual Studio Code or any other modern code editor
 - **Web Browser** – Google Chrome, Mozilla Firefox, Microsoft Edge
- Additional Libraries and Tools:**
- **Node Package Manager (NPM)** – This will be used to manage the dependencies of the project and install the required packages [8].
 - **Axios / Fetch API** – This will be used to send HTTP requests between the frontend and the backend services [9].
 - **JWT (JSON Web Token)** – This will be used to securely authenticate the user sessions.
 - **Cloud Storage Services** – This will be used to store the menu images and other static content efficiently [10].

V. METHODOLOGY

The block diagram represents the overall workflow and interaction structure of the Canteen Order Management System. The block diagram shows the workflow between

two main entities of the system, namely Customers (Students, Faculty, and Staff), and Administrators (Canteen Staff). Both of them start by accessing the system through a common web interface, which enables them to efficiently use the services provided by the Canteen. Depending upon their role and verification, they are then taken to either the User Portal or the Admin Panel. The methodology provides a structure to the workflow of the system for efficient order processing, token generation, and delivery [4][5].

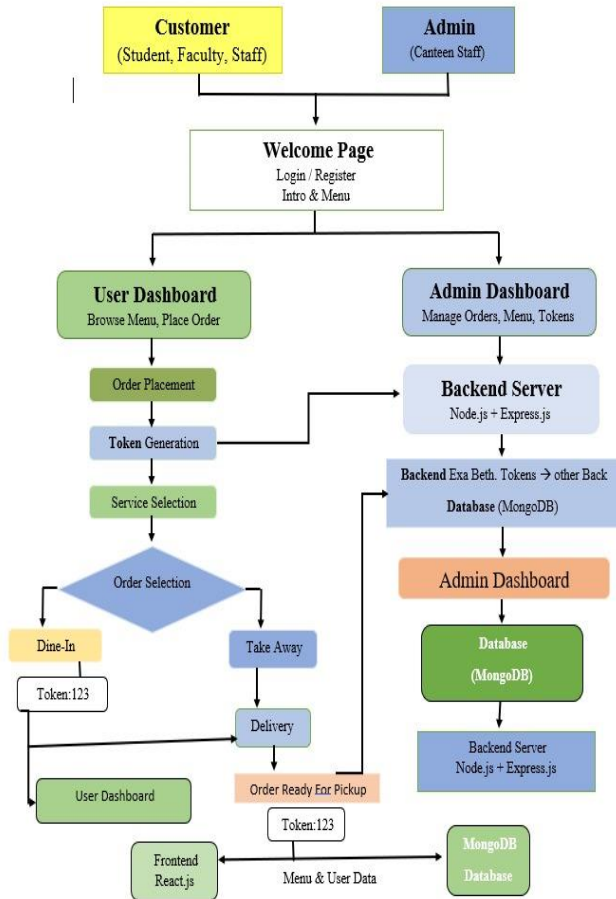


Fig.2. Core Components

The workflow of the proposed system can be categorized into two major categories: Users and Administrators. They use a unified interface for access.

1. Welcome Page:

This is the first page of the system that a user would encounter when accessing the canteen page. It is a brief introduction to the service provided.

2. Get Started / Login:

From the welcome page, users proceed to the login interface. Registered users can enter their credentials, while new users may register before accessing the system.

3. User Login:

In the login page, the user is required to enter his/her registered email and password. After verification, the user is redirected to the User Dashboard.

4. User Authentication:

In the user authentication process, the entered login details are verified using authentication mechanisms. After verification, the user is granted safe access to the system and can continue with the ordering process for food items.

5. User Dashboard / Menu Browsing:

In the user dashboard, the customers can browse through the available menu items and add the items to the cart.

6. Admin Panel:

If the admin enters the correct admin details, they are redirected to the Admin Dashboard. In the admin dashboard, all the orders and token numbers are displayed.

7. Order Placement:

The users place their orders after selecting the food items. The system generates a unique token number for each order and stores the order details in the database.

8. Service Selection (Dine-In / Delivery):

The users can select their order to be delivered in the following two ways:

- **Dine-In** – The customer can collect their order from the counter of the canteen after their token is ready.
- **Delivery** – The faculty/staff can opt for the order to be delivered to their office rooms/department within the campus.

9. Order Management and Monitoring

The admin can monitor all orders, update the order preparation status, and update menu items. After preparing the order, the admin will update the order status to 'Ready'.

10. Order Completion:

Once the order status is updated to 'Ready', a notification is sent to the customer. The customer can collect their order from the counter using their token number. Alternatively, they can opt for delivery of their order.

This structured methodology facilitates smooth order flow, reduced waiting times, smooth token-based queue management, and improved canteen service management within the campus scenario [3].

VI. ACTUAL OUTPUT

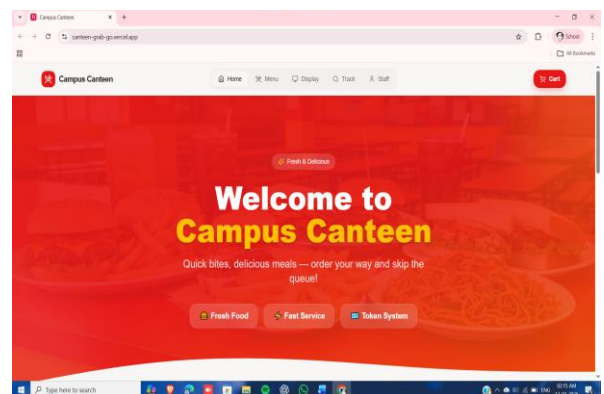


Fig. 3. Home Page

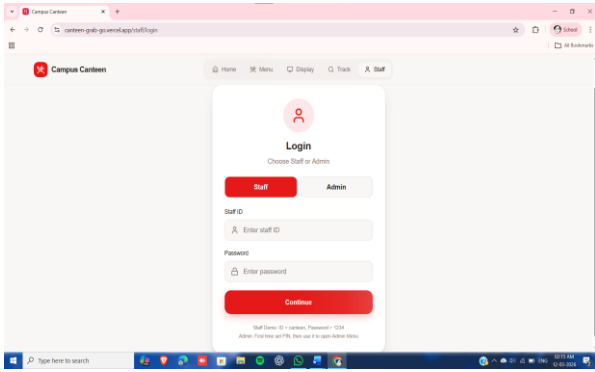


Fig. 3. Login Page

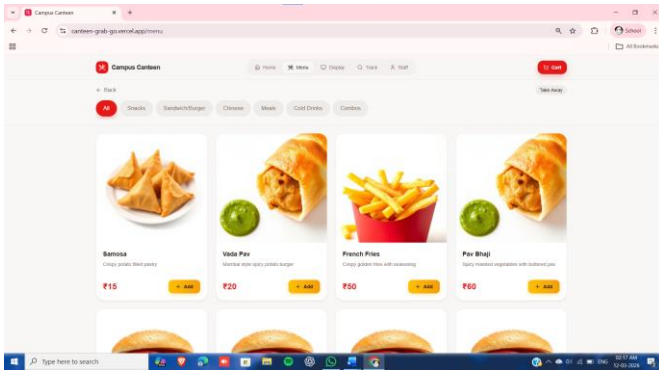


Fig. 4 Menu Page

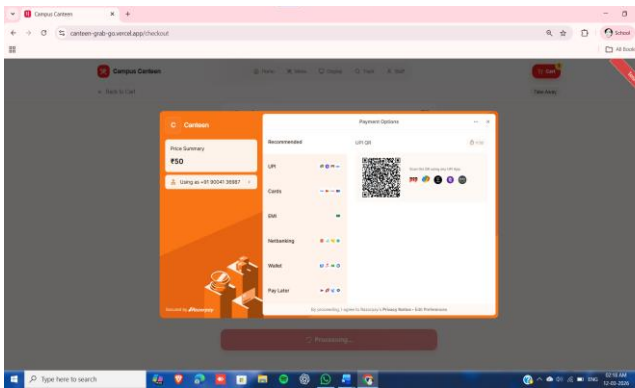


Fig. 5. Payment Gateway

VII Conclusion

The Canteen Order Management System has been successfully developed to offer an efficient and convenient platform for handling food orders within a campus scenario. Generally, traditional canteen systems are often characterized by difficulties during peak hours, including long queues and overcrowding. The proposed system has addressed this problem through the provision of a system whereby students, as well as faculty members and staff, can place their orders using a web-based system. The system has introduced a digital token-based system to efficiently manage orders and avoid overcrowding around the canteen counter.

The system caters to two types of user roles: Customer and Admin. Both of these user roles help in making the overall workflow of the canteen easier. Customers can view the menu items and order food online. They can select between dine-in and delivery depending on their preference. The system provides a unique token number for each order, making it easier for customers to know how their food is being prepared. On the other hand, the Admin Panel helps canteen staff in monitoring orders, menu items, order status, and token queue.

The implementation of this system using the **MERN Stack (MongoDB, Express.js, React.js, and Node.js)** is scalable and efficient enough to run modern-day web applications. The platform is helpful as users can place orders from anywhere within the campus, which includes classrooms, libraries, and offices, thereby becoming more convenient and saving time. The system is user-friendly, scalable, and efficient enough to run modern-day canteen service management.

VIII. FUTURE SCOPE

- **Mobile Application Development:** A mobile application specifically designed for the Android and iOS platforms can also be developed to increase accessibility and convenience. A mobile app would enable students and staff to order quickly using their mobile devices and also provide them with timely information regarding their order status [12].
- **Notification and Alert System:** SMS, email, or even push notification services can also be integrated into this system to provide users with information regarding their order status, i.e., whether it is being prepared or is ready to be collected/delivered. This would also reduce the waiting time of users [2].
- **QR Code Based Ordering:** The system can also be extended to include a QR code-based ordering system within the campus, which would enable users to scan a QR code fixed at a classroom, cafeteria, or other places and directly navigate to the menu page to order food [4].
- **AI-Based Demand Prediction:** The system can be further extended to include AI-based demand prediction, which would enable the system to analyze order patterns and predict which food items are in demand at a given time of the day. This would enable canteen staff to prepare food in advance.
- **Advanced Delivery Management:** The system can also be extended to include intelligent delivery management, which would enable staff to deliver food to users based on their location within the campus. This would enable faster delivery of food to faculty and staff [6].

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3-D Model Generation Using Multi-View and Multi-Data

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Abstract – The fundamental challenge in 3D reconstruction is generating accurate and detailed models from limited and heterogeneous data sources. Traditional single-view approaches suffer from incomplete geometry, low depth accuracy, and poor visualization quality. This paper presents an approach for 3D model generation using multi-view and multi-data integration to improve reconstruction accuracy and visual realism. The system utilizes multiple overlapping images along with Digital Elevation Models (DEM) and satellite imagery. Photogrammetric techniques including Structure-from-Motion (SfM) and Multi-View Stereo (MVS) are used for depth estimation and dense point cloud generation, followed by surface reconstruction and texture mapping. Experimental results demonstrate improved depth estimation, model completeness, and visualization quality compared to single-view methods.

Keywords- 3D Reconstruction; Multi-View Stereo (MVS); Structure-from-Motion (FM); Data Fusion; Digital Elevation Model (DEM); Remote Sensing; Point Cloud; Photogrammetry.

I. INTRODUCTION

Recent advancements in computer vision and geospatial technologies have enabled generation of detailed 3D models from satellite data. However, single-view methods fail to capture complete geometry, while LiDAR-based techniques are costly. This work adopts a multi-view and multi-data approach by combining images from different viewpoints with datasets such as DEM to improve depth estimation and accuracy. Photogrammetric techniques such as SfM and MVS are used to generate 3D point clouds followed by mesh generation and texture mapping. The system aims to improve accuracy and visualization quality while remaining cost-effective.

II. LITERATURE SURVEY

Various techniques have been developed for 3D reconstruction using multi-view and multi-data approaches. Deep learning-based methods provide high accuracy but require high computational resources. Multi-view and multi-sensor approaches improve reconstruction accuracy but increase system complexity and cost. Traditional satellite-based methods provide reliable results but require careful parameter tuning. Overall, existing methods highlight trade-offs between accuracy, cost, and computational complexity, emphasizing the need for efficient approaches.

III. METHODOLOGY

The proposed methodology integrates multi-view imagery and multiple datasets for accurate reconstruction. The process begins with acquisition of satellite images along with DEM and vector datasets. The workflow combines photogrammetry, computer vision, and geospatial data processing, as illustrated in Fig. 3.1.

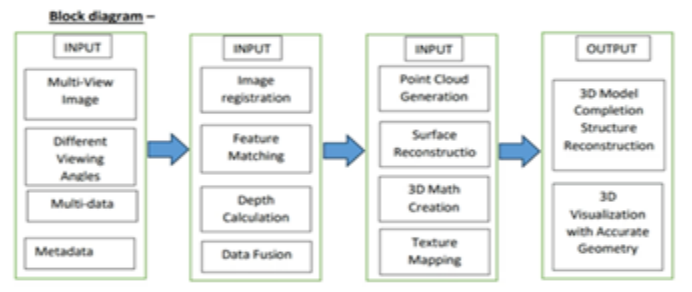


Fig. 3.1: Block diagram of proposed 3D model generation system

These datasets provide sufficient overlap and structural information required for accurate reconstruction. Preprocessing includes radiometric correction, noise removal, and alignment of datasets. Feature extraction and matching are performed using techniques such as SIFT or SURF. Image registration and depth estimation are then applied, followed by data fusion to enhance accuracy.

Feature extraction and matching are then carried out using techniques like SIFT or SURF to detect and match key points across images. Robust filtering methods are applied to remove incorrect matches, improving reliability.

Next, image registration and depth estimation are performed to align images and compute spatial information. Data fusion combines multiple datasets to enhance accuracy and completeness.

The reconstruction phase includes point cloud generation, surface reconstruction, mesh creation, and texture mapping. The model is visualized using tools such as QGIS and validated using reference datasets like DEM.

IV. DATASETS USED

The accuracy of 3D model generation depends on the quality of input datasets. In this work, a multi-view and multi-data

approach integrates satellite data from different Earth observation platforms, providing complementary information such as texture, elevation, and structural details for improved depth estimation and visualization. The datasets include Sentinel-1 SAR, Sentinel-2 optical imagery, Bhuvan geospatial data, and high-resolution WorldView-3 imagery.

1) Sentinel 1 Dataset:

Sentinel-1 is a radar-based Earth observation satellite mission developed by the European Space Agency that provides Synthetic Aperture Radar (SAR) data. It can capture images irrespective of weather conditions such as clouds, rain, or fog, and operates effectively during both day and night, making it reliable for continuous monitoring of the Earth's surface.

Fig. 4.1 shows a sample Sentinel-1 SAR dataset used for terrain and surface analysis.

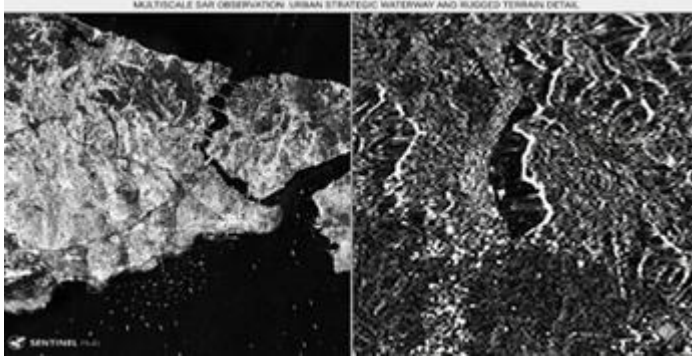


Fig. 4.1 : Sentinel-1 SAR image showing terrain structure and surface variations

The Sentinel-1 dataset is useful for detecting surface characteristics such as roughness, moisture content, and structural variations, and plays an important role in terrain analysis and elevation mapping, especially in areas where optical data is limited. In 3D reconstruction, it contributes to improving elevation estimation and generating more accurate Digital Elevation Models (DEM).

1) Sentinel-2 Dataset

Sentinel-2 is an optical imaging satellite mission also developed by the European Space Agency.



Fig. 4.2 : Sentinel-2 optical image showing land cover and terrain features

It provides high-resolution multispectral imagery across multiple spectral bands, ranging from visible to near-infrared

wavelengths. These images are widely used for land cover classification, vegetation analysis, and feature extraction due to their rich spectral and spatial information.

2) Bhuvan Dataset (ISRO)

Bhuvan is an Indian geospatial platform developed by the Indian Space Research Organisation, designed to provide satellite imagery and thematic datasets for the Indian region. It offers geospatial layers including terrain data, land-use and land-cover maps, infrastructure details, and administrative boundaries.

Fig. 4.3 shows a sample Bhuvan dataset used for regional mapping and geospatial analysis.



Fig. 4.3: Bhuvan geoportal dataset showing terrain and land-use information

The Bhuvan dataset is useful for incorporating region-specific geographical information, enhancing the contextual accuracy of the generated 3D model. It supports integration of local datasets such as road networks, building footprints, and environmental features that may not be available in global datasets.

3) WorldView-3 Dataset

WorldView-3 is a high-resolution Earth observation satellite operated by Maxar Technologies. It is one of the most advanced commercial satellites, capable of providing high-resolution imagery with spatial resolution up to approximately 0.3 meters. It captures both multispectral and panchromatic images, enabling detailed observation of surface features.

Fig. 4.4 shows a sample WorldView-3 dataset highlighting high-resolution urban features.

The dataset is suitable for precise 3D reconstruction, especially in urban environments where fine structural details such as buildings, roads, and infrastructure elements are required. Its high resolution allows accurate modelling of complex scenes, improving both geometric accuracy and visual realism of the generated 3D models. However, due to its commercial nature, access to WorldView-3 data is restricted and requires authorization or purchase, which limits its use in academic projects.



Fig. 4.4 : WorldView-3 high-resolution satellite image showing urban structures

In this Paper, the primary dataset used for implementation is Sentinel-2 imagery due to its free availability and sufficient resolution for 3D reconstruction. Although WorldView-3 provides high-resolution data, it is not freely accessible and requires authorized access. Therefore, due to data availability constraints, WorldView-3 imagery could not be utilized in the implementation.

V. SOFTWARE AND TOOLS USED

The development of the 3D model generation system is performed using a set of geospatial and photogrammetric software tools. These tools assist in various stages such as data preprocessing, reconstruction, visualization, and analysis. The chosen software enables efficient processing of large datasets and helps in producing accurate and realistic 3D models.

1) SNAP (Sentinel Application Platform)

SNAP is a remote sensing software developed by the European Space Agency for processing data obtained from Earth observation satellites, particularly Sentinel missions. It supports both SAR and optical imagery and provides tools for efficient data analysis and visualization (Fig. 5.1).

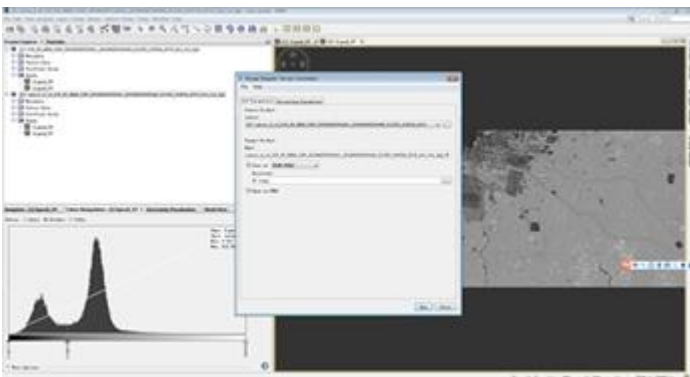


Fig. 5.1: SNAP software interface showing preprocessing and terrain correction

Fig. 5.1 shows the SNAP platform used in this work, including the software interface and preprocessing operations such as terrain correction and raster data visualization.

In this paper SNAP is used to preprocess satellite datasets and generate elevation models for 3D reconstruction. The workflow includes data import, radiometric calibration, speckle noise filtering, and terrain correction to align data with real-world coordinates.

SNAP is also used to generate DEM, DTM, and DSM, which represent terrain elevation and surface features. These models are visualized using grayscale or color gradients to identify features such as slopes and valleys and are exported for further visualization and analysis in QGIS.

2) QGIS (Quantum Geographic Information System)

QGIS is a powerful open-source Geographic Information System used for spatial data analysis, mapping, and 3D visualization. It provides a flexible environment for integrating multiple datasets and generating detailed geospatial models.

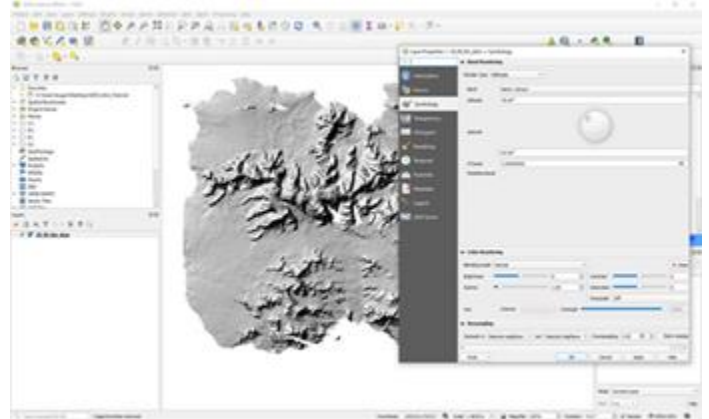


Fig. 5.2: QGIS interface showing DEM visualization and 3D terrain modelling

Fig. 5.2 shows the QGIS is utilized as the primary platform for integrating processed datasets and generating the final 3D model. Raster datasets such as DEM, DTM, and DSM obtained from SNAP, along with satellite imagery and vector data (e.g., roads and building footprints), are imported and aligned using a common coordinate reference system to ensure spatial consistency. The 2D interface enables effective visualization of multiple layers, where elevation data is represented using grayscale or color gradients, while satellite imagery provides real-world context and vector layers enhance structural representation. The 3D Map View functionality facilitates the transformation of 2D datasets into a three-dimensional environment, where the DEM serves as the base surface and elevation values define terrain height, with satellite imagery draped over the surface to improve visual realism and vector layers extruded to represent built structures. Additionally, the

Qgis2threejs plugin is used to generate interactive 3D visualizations, allowing user interaction through rotation, zooming, and perspective exploration. QGIS also provides analytical tools such as slope analysis and elevation profiling, which support the evaluation of terrain characteristics and model accuracy.

VI. RESULTS

The results demonstrate that integrating multi-view imagery and multi-data sources enables accurate terrain modelling and effective 3D visualization. Using SNAP and QGIS, elevation models, hydrological features, and 3D representations were successfully generated

A. Digital Elevation Model (DEM) Analysis

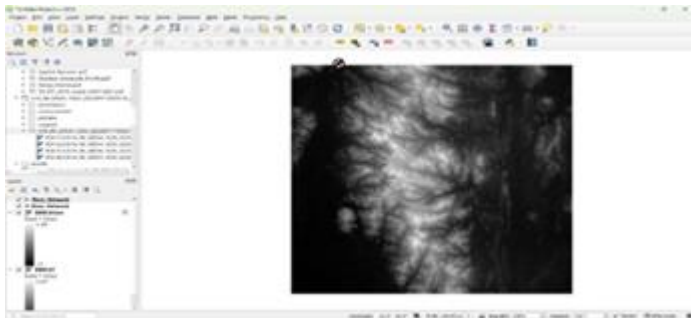


Fig. 6.1 Digital Elevation Model (DEM) Visualization in QGIS

As shown in Fig. 6.1, The DEM was visualized in QGIS using grayscale, where brighter areas indicate higher elevations and darker areas represent low-lying regions. It clearly highlights terrain features such as ridges, slopes, and valleys, proving its reliability for further analysis.

B. DEM Visualization with Map

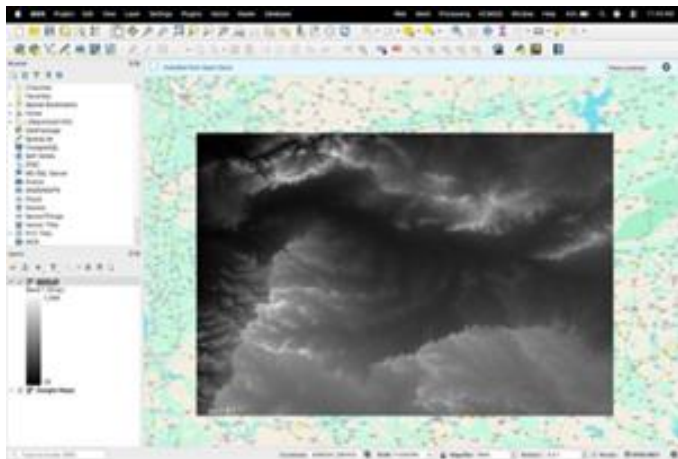


Fig. 6.2 DEM Visualization with Basemap

As shown in Fig. 6.2, Overlaying the DEM on a basemap improves spatial understanding by linking elevation data with real-world locations like roads and settlements, enhancing interpretability.

C. River Network Extraction

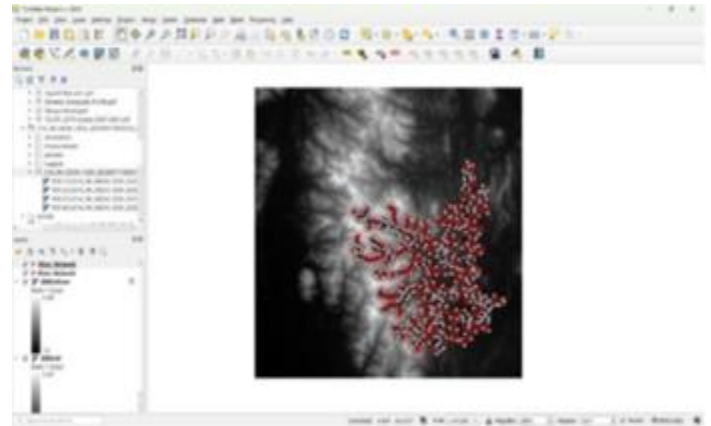


Fig 6.3 River Network Extraction

As shown in Fig. 6.3, Hydrological analysis using flow direction and accumulation techniques enabled extraction of river networks. The results accurately represent drainage patterns and water flow behaviour.

D. 3D Terrain Visualization

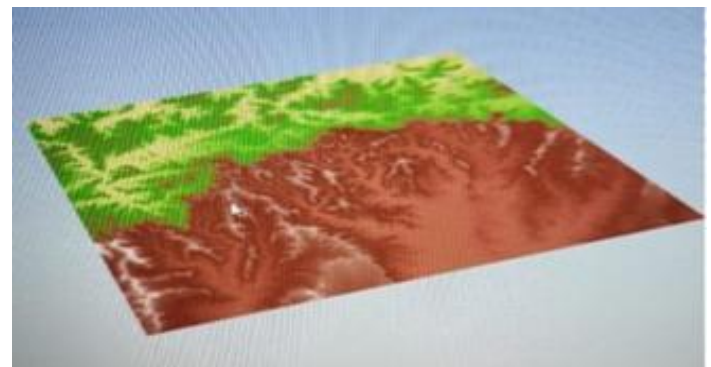


Fig 6.4 3D Elevated Image

As shown in Fig. 6.4, A 3D model generated in QGIS provides a realistic view of terrain using elevation-based colour gradients. It improves spatial perception and understanding of terrain structures.

As shown in Fig. 6.5, DTM represents bare-earth terrain, while DSM includes surface features like buildings and vegetation. Their comparison helps distinguish natural and man-made structures, improving 3D model accuracy.

E. DTM and DSM Analysis

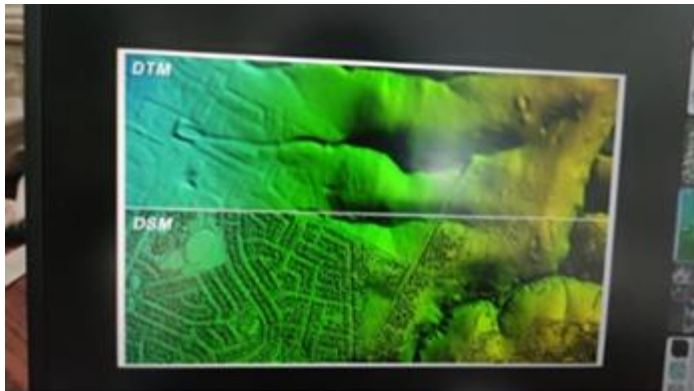


Fig 6.5 DTM and DSM in QGIS/SNAP Software

VII.CONCLUSION

This work presents a 3D model generation approach using multi-view imagery and multi-data sources. By integrating satellite data and elevation models (DEM, DTM, DSM) with photogrammetry and geospatial analysis, accurate and realistic terrain models are generated. Results show improved depth estimation, visualization, and model completeness compared to traditional methods. The use of SNAP and QGIS makes the approach cost-effective and practical. The generated models are useful for applications such as urban planning, environmental monitoring, and disaster management. Future improvements can include deep learning and higher-resolution data for better accuracy.

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An Integrated AI-Driven System for Crop Recommendation and Plant Disease Detection

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To begin with, agriculture is a major economic component in India's development as well as source of income for the majority of Indians. However, despite all the benefits, agriculture faces numerous problems which include proper selection of plants, optimal application of fertilizers, and plant diseases identification. These aspects are causing low levels of production and slow degradation of soil properties. Therefore, the current project proposes a framework, based on artificial intelligence and including such aspects as crop recommendation, fertilizer optimization, and disease detection. The system examines the essential parameters related to the soil such as its nitrogen level, phosphorous content, potassium amount, pH level, and moisture as well as other factors like temperature and rainfall. On the basis of the data provided by the system, appropriate crop and fertilizers are chosen. Machine learning methods are used for the prediction in order to make accurate recommendations regarding crop and fertilizers. Moreover, deep learning methods, especially Convolutional Neural Network (CNN) is applied for the plant disease detection based on the leaf image analysis. Thus, it can help to detect the plant disease in time. As a result, the project aims to assist both novice and professional farmers with intelligent decisions about agricultural activities.

Index Terms—Artificial Intelligence (AI), Machine Learning (ML), Precision Agriculture, Crop Recommendation, Plant Disease Detection, Convolutional Neural Network (CNN), XGBoost, EfficientNetV2

I. INTRODUCTION

It should not be forgotten that agriculture is currently among the leading industries all over the world, being the major source of food supply and job creation. In particular, agriculture plays an important role in the economies of developing countries like India since many people earn their living in agriculture. Moreover, due to climate changes, the development of innovative agricultural approaches becomes necessary. Nevertheless, many problems arise when data analysis is required for selecting the proper type of crops, using fertilizers, and diagnosing diseases in plants. Traditional approaches based on people's experience and intuition can cause serious difficulties, including the improper choice of crops, inefficient usage of fertilizers, and incorrect diagnostics. Given the growing availability of data related to agriculture, machine learning (ML) and deep learning (DL) models are widely used in smart farming.

The recent research shows that it is possible use ML algorithms to predict the most appropriate types of crops

by analyzing the nitrogen (N), phosphorus (P), potassium (K), pH, temperature, humidity, and precipitation [3], [4]. Moreover, such ensemble learning algorithms as XGBoost showed extremely good performance, as they can predict the crop with extremely high accuracy due to the ability to establish the complicated non-linear relations between soil and climatic factors [5]. Also, the recent progress in the field allowed creating efficient CNN-based networks, such as ResNet50 and EfficientNetV2, which can detect different plant diseases with over 95% accuracy in the majority of cases. However, while many problems were solved separately, for example, crop recommendation [8], [9] or disease detection [10].

An obvious drawback of the current state of affairs in the field under discussion is the absence of a combined algorithm that would help solve more than one problem at once. In addition, while the choice of crops and disease diagnosis are quite relevant issues, fertilization remains vital since it allows maintaining the high soil fertility. At the same time, farmers do not always have the opportunity to conduct thorough tests of the soil and receive nutrient-based recommendations for fertilizers.

To address this issue, the paper suggests considering the combination of machine learning and deep learning methods that will be used in a hybrid model of the smart farm to help with crop recommendation, plant disease detection, and fertilizer optimization.

This hybrid solution will contain the following elements. First, the crop recommendation module will utilize the supervised ML models, such as XGBoost, to predict

II. LITERATURE SURVEY

Lately, there's been a lot more use of machine learning and deep learning in farming stuff. It helps with things like suggesting what crops to plant, guessing yields, and spotting diseases early on plants. I think the big deal is how these methods use data to make decisions automatically, without needing all that costly equipment or fancy setups. So researchers keep trying them out to boost productivity and make farming more sustainable, you know.

One project that stood out was this web thing called Harvestify. They threw in algorithms like Decision Tree, Random

Forest, Naives Bayes, and XGBoost for recommending crop and fertilizers. The way they combined them into an ensemble got up to 99.01% accuracy, which seems way better than just picking one algorithm. But it mostly stuck to looking at soil nutrients, and skipped over detecting plant diseases altogether.

Then there was this other work that mixed machine learning with deep learning for managing agriculture in a sustain- able way. They used Random Forest and XGBoost for crop suggestions, and for diseases, they went with CNN models like ResNet50 and EfficientNetV2. It hit about 99% for crop prediction and 96.06% for classifying diseases. The framework pulled together data from tables and images, which is cool, but it relies on tons of environmental info and sensors. That might make it tough for smaller farmers to actually use.

On yield prediction, some research built an ensemble setup with multiple classifiers. It beat out the usual regression methods and single algorithms every time. Kind of shows how ensembles can grab onto those tricky patterns in agriculture data.

For detecting plant diseases, another study ran deep CNNs and got 97.16% accuracy with ResNet50. There was also this system using machine learning plus image processing, analyz- ing colors and textures on leaves. These CNN approaches pick up on small changes in leaf patterns pretty well, so diagnosing diseases gets faster and more spot on.

All this points to progress in separate areas, like recommen- dations, yields, and diseases. But most stuff handles them one at a time, which feels fragmented. I am not totally sure, but it seems like we need something that ties it all into one system farmers can easily access. That way, decisions could be more informed and help with sustainability, though its not clear how to make that happen without complications.

- Hybrid setups mixing machine learning and deep learning models tend to give better accuracy. They also handle generalization well in farming uses.
- Ensemble models really stand out. Things like Random Forest and XGBoost keep doing better than other classi- fiers. They are robust. Plus, they resist overfitting pretty well.
- When it comes to image analysis, CNN architectures lead the way. Deep ones such as ResNet50 and EfficientNetV2 work effectively for spotting diseases. They hit high precision across various plant types.
- Most of this is data-driven. Studies stress that you can get solid predictions from open datasets. No need for IoT sensors at all. That makes these approaches more affordable and scalable too.

All these findings point to the promise of data-driven hybrid ML- DL frameworks. They help create efficient decisionsup- port systems for agriculture. Ones that are accessible and sustainable. This current work builds on that. It combines crop recommendations with plant disease predictions. All in one model that skips sensors. Trained on public datasets

III. METHODOLOGY

This framework is basically a mix of machine learning and deep learning to help with decisions in farming. It uses machine learning stuff for suggesting what crops to plant. Then deep learning comes in for spotting diseases on plants and predicting them too. I think combining those makes it more useful overall.

The system pulls from two kinds of data. One is about soil and things like weather or environment. The other is pictures of plant leaves. By putting those together, it should give better automated advice for farmers, or at least thats the idea. It seems accurate enough from what Ive seen in similar things. Now the way it works starts with getting the data. Pre- processing comes next to clean it up and make sure its consistent. After that, you build and train the models on this data. Evaluation is the last part to check how well it performs.

Some steps might overlap a bit, I am not totally sure. That part gets a bit messy when you try to implement it.

Overall, it aims to make agriculture smarter without too much manual work.

A. System Overview

1. Crop Recommendation Module – predicts the most suitable crop based on soil and climatic attributes.
2. Plant Disease Prediction Module – classifies plant leaf images into healthy or diseased categories using deep learning models.

B. Data Collection

1.Crop Recommendation Dataset: The crop recommenda- tion dataset comprises a range of numerical attributes that characterize soil and environmental conditions. These features include Nitrogen (N), Phosphorus (P), Potassium (K), soil pH, temperature, humidity, and rainfall. Each record is associated with a target label indicating the most suitable crop for the given conditions, such as rice, maize, banana, or cotton. The dataset was sourced from publicly accessible repositories, in- cluding Kaggle, as well as from previously published research studies [1], [2].

2.Plant Disease Dataset: For the purpose of plant disease identification, the widely recognized PlantVillage dataset was utilized. This dataset contains thousands of annotated images of plant leaves from various crops, including tomato, maize, grape, and orange. Each image is labeled to indicate whether the leaf is healthy or affected by a specific disease, such as bacterial spot, late blight, or powdery mildew. The diversity and high-quality annotations of this dataset make it well- suited for training and evaluating deep learning models for accurate disease classification.

C. Data Processing

1. Crop Dataset Preprocessing

We started by cleaning up the crop dataset. Whenever data was missing, we didn't just leave it blank—we filled in the gaps with either the average or the median, depending on how the data looked. Then, we leveled the playing field for all the numbers by scaling everything between 0 and 1 using Min-Max normalization. To make sure our models could actually use the crop types, we converted those names into numbers with label encoding. In the last step, we split the data, saving 80% for training and 20% for testing how well the model performs.

2. Image Dataset Preprocessing

For the plant leaf images, we resized every photo to 224 by 224 pixels so they'd fit with well-known neural networks like ResNet50 and EfficientNetV2. We didn't just rely on the pictures as they were—we mixed things up using data augmentation. That means we randomly rotated, flipped, zoomed, and shifted the images, giving the model a chance to learn from more varied data without needing extra photos. After that, we scaled the pixels down between 0 and 1 to smooth out the learning process. Finally, we split the images into 80

D. Model Training and Evaluations

Training the models is a big deal when it comes to getting the crop recommendation and plant disease prediction systems working accurately and reliably. Since tabular and image data aren't much alike, I set up separate training pipelines for the machine learning (ML) and deep learning (DL) sides of things.

1) Crop Recommendation Model Training

I ran several supervised ML algorithms on the cleaned-up crop dataset: Decision Tree, Naïve Bayes, SVM, Logistic Regression, Random Forest, and XGBoost all took a shot. I made sure to scale and normalize the data so everything played nice—this helps the models learn faster and predict better.

For tuning, I leaned on Grid Search Cross-Validation. It walked through different hyper parameter settings and nailed down the best combination. This kept the models solid and kept over fitting in check.

After the dust settled, Random Forest and XGBoost stood out. Random Forest handled overfitting really well—it blends together a bunch of decision trees, so it stays stable and accurate. XGBoost, on the other hand, was quick and generalized surprisingly well. Its gradient boosting lets it sniff out tricky, non-linear patterns in the data.

2) Plant Disease Prediction Model Training

For plant diseases, I started with deep learning models built for images—ResNet50 and EfficientNetV2. I didn't train them from scratch. Instead, I used transfer learning: I grabbed pre-trained weights from ImageNet and then fine-tuned them on the PlantVillage dataset. This way, the models quickly picked up on things like leaf texture, shape, and color that matter when spotting diseases.

To get the best results, I used the Adam optimizer and categorical cross-entropy loss, which fits multi-class classification perfectly. I also used early stopping and adjusted the learning rate as training went along, which kept things efficient and kept the models from overfitting. On top of that, I tossed in real-time data augmentation—rotating, flipping, and scaling images during training—to help the models generalize and not just memorize the dataset quirks.

E. Deployment and Integrations

Web-Based System Integration

To make things easier and more accessible, we brought all our trained machine learning and deep learning models together into one web-based platform, built with Python Flask. Now, users can interact with these predictive tools easily, right from their browsers. Real-time agricultural decision-making gets a whole lot simpler, thanks to the site's straightforward, intuitive layout.

1) Crop Recommendation Interface

For crop recommendations, we kept the interface clean and simple. Users just plug in the key details—Nitrogen, Phosphorus, Potassium, pH, temperature, humidity, and rain-fall. As soon as you hit submit, the machine learning model crunches the numbers and recommends the most suitable crop. It even shows you the probability scores, so you know how confident the model feels about its pick. Farmers, students, and researchers can all get solid, science-based suggestions quickly, without any hassle.

2) Plant Disease Detection Interface

Diagnosing plant issues is easy here. You just upload a leaf photo, and the system's convolutional neural network goes to work. It tells you right away whether the plant is healthy or what disease it's dealing with. Getting answers is fast, which gives farmers a head start on solving problems and keeping their crops healthy.

3) Integration Features and Accessibility

We built the platform around public datasets, so nobody needs expensive sensors or specialized gadgets to use it. The whole thing runs light—you can set it up on a personal computer or launch it in the cloud with minimal fuss. And if you need it on the go, you can extend everything to a mobile app for in-field use. That kind of flexibility makes it easy to scale up or adapt to different farm settings, giving the entire solution some real staying power in the agricultural world.

F. Results and Discussions

A. Crop Recommendation Results: We tested a bunch of machine learning algorithms to figure out which crops would work best in different soils and environments. The list included Decision Tree, Naïve Bayes, SVM, Logistic Regression, Random Forest, and XGBoost. After comparing them, XGBoost came out on top—it just predicted the outcomes more accurately than the others. On top of that, it didn't just memorize the training data; it really handled new situations well. Its gradient boosting approach helped avoid overfitting, which means the predictions stayed solid and didn't fall apart when we changed up the input data.

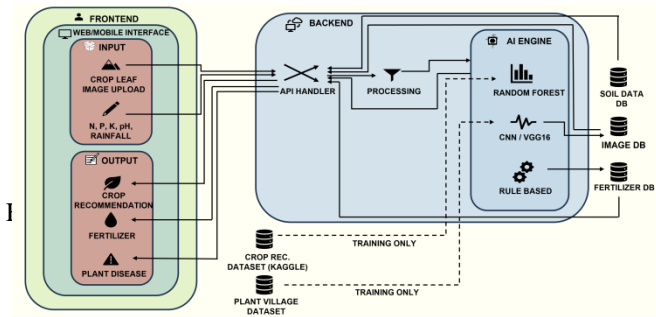


Fig. 1. System Architecture

TABLE I
COMPARATIVE PERFORMANCE OF ALL IMPLEMENTED MACHINE LEARNING MODELS

Model	Accuracy(%)	Precision	Recall	F1-Score
Decision Tree	90.12	0.84	0.88	0.85
Naïve Bayes	87.25	0.82	0.81	0.81
SVM	92.84	0.90	0.89	0.89
Classification	88.76	0.83	0.85	0.84
XGBoost	99.03	0.99	0.99	0.99

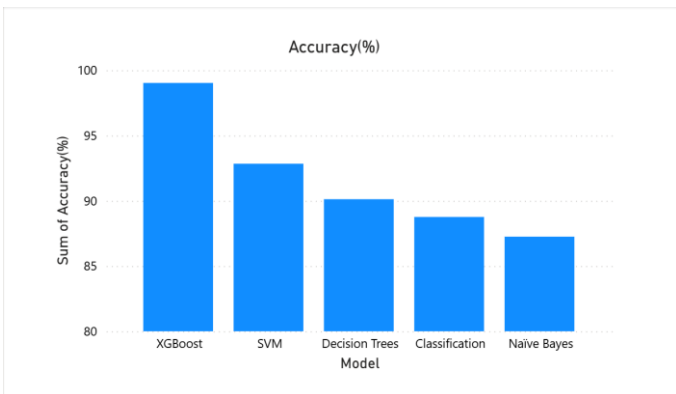


Fig. 2. Insights of Model Accuracies

The experiments show that ensemble learning methods, especially Extreme Gradient Boosting (XGBoost), leave single machine learning models in the dust. These approaches handle the tricky, non-linear ties between soil nutrients—nitrogen, phosphorus, and potassium—and environmental factors like temperature, humidity, and rainfall. Because of this, they predict crop suitability with impressive accuracy. The model’s F1-score hit 0.99, which basically means it nails both precision and recall. This kind of performance really proves how reliable and tough the method is, making it a solid choice for anyone looking to use it in real-world farming

B. Plant Disease Detection Results:

For plant disease prediction, we used two advanced deep learning models ResNet50 and EfficientNetV2. Both relied on

transfer learning, starting with weights pre-trained on ImageNet and then fine-tuning on the Plant Village dataset. This dataset includes all kinds of healthy and diseased leaf images from different crops. We trained the models with the Adam optimizer and used categorical cross-entropy as the loss function to handle the multi-class classification.

Both models performed really well, but EfficientNetV2 came out on top, hitting a classification accuracy of 97.12%. It edged out the other CNNs, thanks to its smart design that adjusts network depth, width, and resolution for better feature extraction. ResNet50 also did a solid job, mainly because its residual connections help avoid the vanishing gradient problem, making it easier to train deeper networks.

The learning curves from validation showed steady convergence—with hardly any over fitting—throughout training. All in all, these results show the deep learning models are robust and can generalize well. That makes them strong candidates for dependable plant disease identification out in the field.

TABLE II
PERFORMANCE OF CNN MODELS FOR PLANT DISEASE DETECTION

CNN Model	Accuracy(%)	Precision	Recall	F1-Score
ResNet50	96.06	0.96	0.96	0.96
Naïve Bayes	97.12	0.97	0.97	0.97

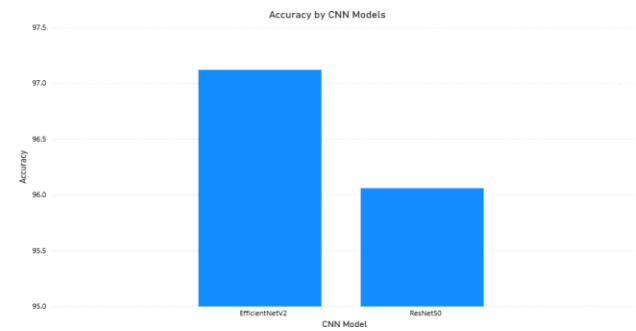


Fig. 3. Performance of CNN Models for Plant Disease Detection.

Comparative Analysis: Machine learning and deep learning each bring their own strengths to agriculture. ML handles structured data well—things like soil nutrients or climate info—so it’s great at predicting which crops to plant or which fertilizers to use. DL, on the other hand, shines with unstructured data, especially images, which makes it the go-to for spotting plant diseases. When you put these two approaches together, you get a more complete and effective tool for precision farming.

In this study, we relied on ensemble-based ML algorithms like Random Forest and XGBoost for crop recommendations. They clocked in at about 99% accuracy, which is impressive. For plant disease detection, we used the EfficientNetV2 deep learning model, which hit roughly 97% accuracy. These results show that mixing ML and DL really works when you’re tackling different types of ag problems. Plus, our system doesn’t rely on fancy sensors or extra hardware. It’s accessible—farmers, students,

researchers, anyone can use it without hefty costs.

Let's talk about what that means in practice. First, Random Forest was our choice for crop and fertilizer suggestions—it handles huge, complex datasets and picks up on tricky patterns most other algorithms miss. That accuracy makes it pretty reliable. When it came to disease detection, we turned to the VGG16 convolutional neural network. Its layered structure is great at spotting subtle differences in plant leaves, so it can accurately tell if a leaf is healthy or diseased. By merging these models, our system doesn't just get more accurate—it gets easier to use and more scalable, cutting out a lot of manual work.

We also built a simple web interface so people can use the system right away. All you need to do is punch in soil and climate details to get crop recommendations, or upload leaf photos for disease detection. Since it works with open datasets, nobody needs to buy new sensors or equipment. That makes it not just practical, but affordable.

So, in the end, our hybrid system is both sustainable and budget-friendly. It helps people make smart, data-driven choices on the farm, boosts yields, saves resources, and catches plant diseases early. In short, it pushes farming toward a smarter, more sustainable future.

IV. CONCLUSIONS

This research introduces a data-driven system that brings machine learning and deep learning together to make precision agriculture smarter. The idea is to handle three big tasks: recommend which crops to plant, spot plant diseases, and fine-tune fertilizer use. The system looks at soil nutrients and environmental factors to suggest the best crops for a given plot. It uses deep learning to scan leaf images and quickly detect diseases. On top of that, it figures out the right fertilizer mix, adjusting for both what's in the soil and each crop's unique needs.

The team relied on ensemble learning algorithms—Random Forest and XGBoost—for crop prediction, and they hit about 99% accuracy. For detecting diseases, they went with the EfficientNetV2 convolutional neural network, which nailed a 97% accuracy rate. The fertilizer module makes smarter recommendations, helping farmers use nutrients efficiently and keep the soil healthy for the long run. Altogether, this hybrid system is fast, reliable, and can easily be scaled up. It's a big step toward data-driven, sustainable farming that's tuned for both high productivity and environmental care.

V. ACKNOWLEDGMENT

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Predictive Analytics for Environmental and Oceanographic Systems

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fishing productivity indices and (ii) evaluating conventional time

Abstract—There exist few static and conventional techniques for identifying productive fishing zones or the Potential Fishing Zone (PFZ), despite the fact that fishing sustains millions of livelihoods and makes a substantial contribution to agricultural GVA in our India. A framework for weekly predictive mapping of high-density fishing zones is presented in this paper. It compares the Spatio-Temporal Encoder-Graph Network (SEGN) against traditional ARIMA/ARIMAX baselines and uses time-series forecasting [1]. It outline deliverables (weekly maps and per-cell error metrics), evaluation metrics, model training, and data preprocessing. To facilitate operational deployment and further research, a reproducible pipeline and example results are presented.

Index Terms—potential fishing zones, time series forecasting, ARIMA, SEGN, spatial analytics, oceanographic data, predictive mapping

I. INTRODUCTION

Fishing activities have considerable significance in the economy of India, as they contribute to the Agricultural Gross Value Added (GVA) to the tune of nearly 6.7% while providing livelihood to about 28-30 million people. However, the location of productive fishing zones was traditionally determined by static maps using rule-based approaches with limited environmental factors.

Recent advances in satellite remote sensing techniques and ocean monitoring systems have allowed for the continuous collection of large-scale oceanographic data [2], [3]. This shift in the availability of data has changed the focus of research in fishing activities from heuristic-based to data-driven predictive models. Recent research in this area has proposed spatio-temporal learning models to employ multiple environmental factors to locate Potential Fishing Zones (PFZs) [4], [5]. Among these models, the Sequential Environmental Gradient Network (SEGN), as proposed by Rele et al. in [1], includes engineered gradient features, seasonal statistics, and temporal modeling to capture the weekly patterns of fishing activities. For example, conventional approaches for identifying fish-ing zones usually involve the thresholding of sea surface temperature and concentrations of chlorophyll [2], [6]. Al-though these methods are successful for localized applications, they cannot account for complex temporal dynamics and environmental interactions.

As a remedy for these limitations, the current study aims to establish models for the prediction of high-density fishing zones on a weekly basis with associated uncertainty estimates. We achieve this by (i) using environmental data for the prediction of weekly

series models such as ARIMA and deep spatio-temporal models such as SEGN [1], [7].

The main contributions of this work are:

- 1) Developing a reproducible workflow for weekly forecasting of fishing effort potential with classical and deep spatiotemporal models.
- 2) Providing an empirical investigation of ARIMA/ARIMAX and SEGN models over spatial cells, including per-cell error analysis.
- 3) Offering a strategic framework for the operational deployment of fishing zone maps for fisheries stakeholders.

II. RELATED WORK

People usually find fishing spots by looking at satellite pictures and adding information they get from the water using simple rules or grouping techniques. Some folks have used ways to look at information that changes over time and space to see how things like water temperature and fishing are related.

Fitrianah et al. [4] used techniques to analyze spatio-temporal oceanographic patterns affecting fisheries in the East-ern Indian Ocean. Majumder et al. [8] showed that machine learning models can effectively identify PFZs in the Indian Ocean.

One more prominent work includes using SARIMA and Random Forest for prediction of Potential Fishing Zones (PFZs) using Machine Learning models. [9]

Recent studies demonstrate increasing adoption of models that integrate environmental variables with spatial and temporal learning [10]. These studies highlight the limitations of single-variable or short-term approaches and motivate the use of sequential models such as SEGN [1].

Fishery landings data has also been modeled using statistical time-series methods such as ARIMA [7]. However, these approaches lack spatial dependency modeling. The SEGN framework addresses this limitation by jointly modeling spatial gradients, seasonal statistics, and temporal dependencies.

III. SEQUENTIAL ENVIRONMENTAL GRADIENT NETWORK (SEGN)

The Sequential Environmental Gradient Network is a computer system that learns where people like to go fishing a lot. It figures this out by looking at how things change in areas what happens during different seasons and how things are connected over time [1].

- **Environmental Processor:** Processes raw oceanographic variables like sea surface temperature, salinity, chlorophyll concentration, and others.
- **Gradient Processor:** Computes spatial and temporal gradients that help detect ocean fronts influencing fish aggregation.
- **Seasonal Processor:** Encrypts seasonal statistics derived from multi-year datasets.

IV. DATA AND PREPROCESSING

Our predictive framework leverages the weekly fishing hours of the actual data for training and predicts the best value. The dataset is compared with fishing activity ground

VI. EVALUATION METRICS

truth values derived from observational records.

Preprocessing steps include: spatial alignment, temporal aggregation, gradient-based feature engineering, and hotspot labeling. These steps ensure fair comparison between ARIMA and SEGN models.

V. METHODOLOGY

This study implements two broadly different predictive approaches:

A. ARIMA Baseline

classical Autoregressive Integrated Moving Average (ARIMA) models is applied on aggregated time series of fishing activity indices in each spatial grid cell. ARIMA models have been widely used in fisheries research to capture seasonality and short-term temporal dependencies in catch and landing data [7]. Their interpretability and low computational cost make them a strong statistical baseline for evaluating the time based data, like fishing hours.

B. SEGN Model Application

The SEGN model described in Section IV is trained using the engineered 192-dim feature vectors as inputs. Training uses a file-based random split to ensure geographical diversity (70% training, 10% validation, 20% test). A weighted cross-entropy loss is applied to mitigate class imbalance, and training is stabilized using the AdamW optimizer with ReduceLROnPlateau learning rate scheduling. Mixed precision training is employed for computational efficiency. Early stopping is triggered based on validation F1-score performance.

We evaluate models using:

- **Regression metrics:** Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE).
- **Classification metrics:** Precision, Recall, F1-score for binary hotspot detection.

Forecasts are compared at the weekly horizon across common spatial cells.

The proposed framework is evaluated using both regression and classification metrics [5]. Regression metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Classification performance is assessed using precision, recall, F1-score, and AUC-ROC to evaluate hotspot detection capability.

A. Regression Metrics

For evaluating the accuracy of weekly fishing activity forecasts, we employ Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These quantify deviations between predicted values \hat{y}_t and ground-truth observations y_t at each spatial grid cell.

$$\text{MSE} = \frac{1}{N} \sum_{t=1}^N (y^t - \hat{y}_t)^2 \quad (1)$$

$$\text{RMSE} = \sqrt{\text{MSE}} \quad (2)$$

$$\text{MAPE} = \frac{100}{N} \sum_{t=1}^N \frac{|y_t - \hat{y}_t|}{y_t} \quad (3)$$

These metrics emphasize both overall predictive accuracy and sensitivity to large forecasting errors, which are critical for operational fishing guidance.

B. Classification Metrics

To assess the ability of the models to correctly identify high-density fishing zones, continuous predictions are converted into binary hotspot labels using a fixed probability threshold. Classification performance is evaluated using precision, recall, and F1-score, defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

These metrics are particularly suitable for the imbalanced nature of fishing hotspot detection, where false positives and false negatives have asymmetric operational costs.

VII. EXPECTED OUTPUTS AND DELIVERABLES

- Weekly map tiles of predicted fishing hours or relative potential score (GeoTIFF / PNG / web tiles).
- Per-cell error metrics and reliability mask (hotspots with low forecast error).
- A reproducible codebase and Jupyter notebooks (or scripts) to generate maps and diagnostics.
- Final report and a short user guide for operational adoption by fishers/cooperatives.

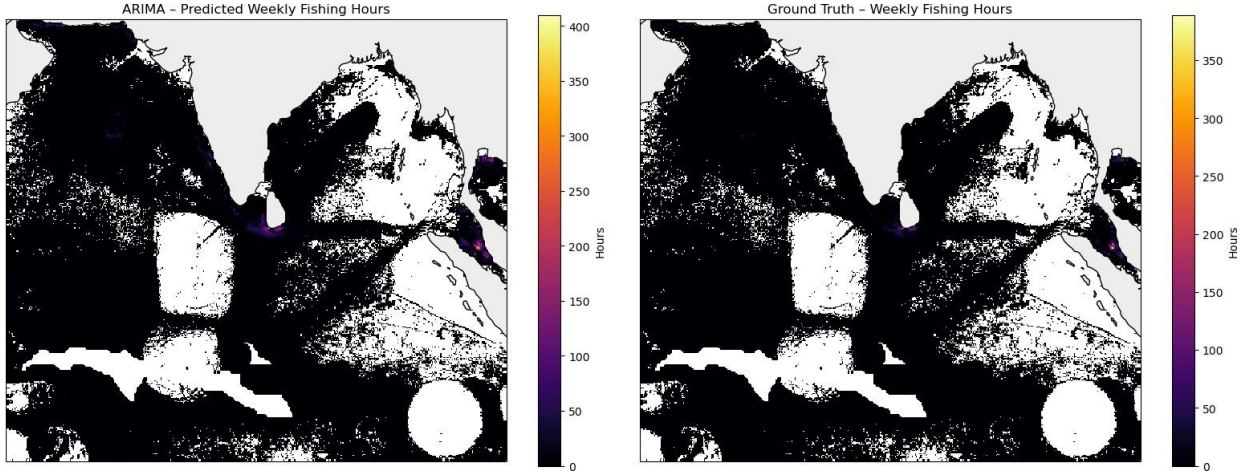


Fig. 1: Comparison between actual fishing activity and ARIMA predictions over time. The model captures temporal trends but exhibits large variance in magnitude.

VIII. RESULTS

Table I summarizes comparative performance between the ARIMA baseline and the SEGN model for the common test set.

TABLE I: Performance comparison between ARIMA and SEGN models.

Metric	ARIMA	SEGN
Accuracy	0.339	0.871
Precision (Fishing)	0.084	0.190
Recall (Fishing)	0.976	0.329
Weighted F1-Score	0.438	0.887
AUC-ROC	0.837	0.755

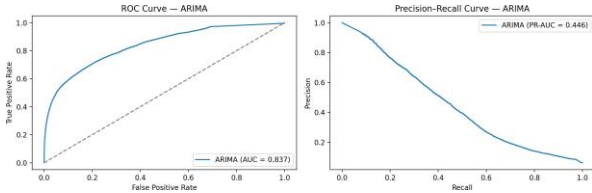


Fig. 2: ROC and Precision–Recall curves for the ARIMA model. While ARIMA achieves a high recall, precision remains low, indicating a tendency to over-predict fishing zones.

As shown in Table I, SEGN significantly outperforms ARIMA in weighted F1-score and precision, while ARIMA exhibits extremely high recall at the cost of excessive false positives. Spatial comparisons in Fig. 4 further demonstrate that SEGN produces more localized and operationally meaningful fishing hotspots.

We can easily conclude that ARIMA is better for regular basis of fishing zone (the Western Coast of India) while SEGN compares in-depth for predictions.

Fig. 2 and Fig. 1 illustrate predictive time-series behavior and classification characteristics, respectively. Overall, SEGN

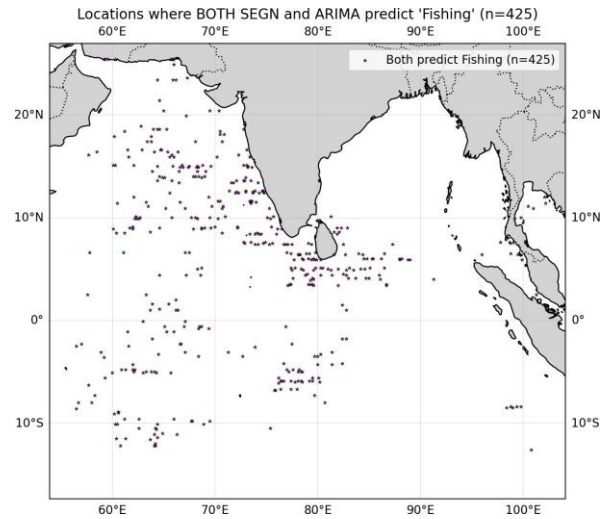


Fig. 3: Spatial regions where both ARIMA and SEGN predict fishing activity. These areas indicate stable fishing zones consistently identified by both models.

demonstrates stronger capacity to model complex environmental interactions and maintain improved classification performance compared to ARIMA.

The results indicate spatial heterogeneity in forecast reliability. Operational deployment requires confidence-aware decision support mechanisms. Still, there are some drawbacks for predictions, these limitations include data sparsity, sensor noise, and reporting bias, which must be considered when interpreting model outputs [3], [5].

IX. CONCLUSION

This study compares classical ARIMA models with the deep spatio-temporal SEGN framework for forecasting fishing activity. SEGN demonstrates superior capability in capturing complex environmental interactions and producing

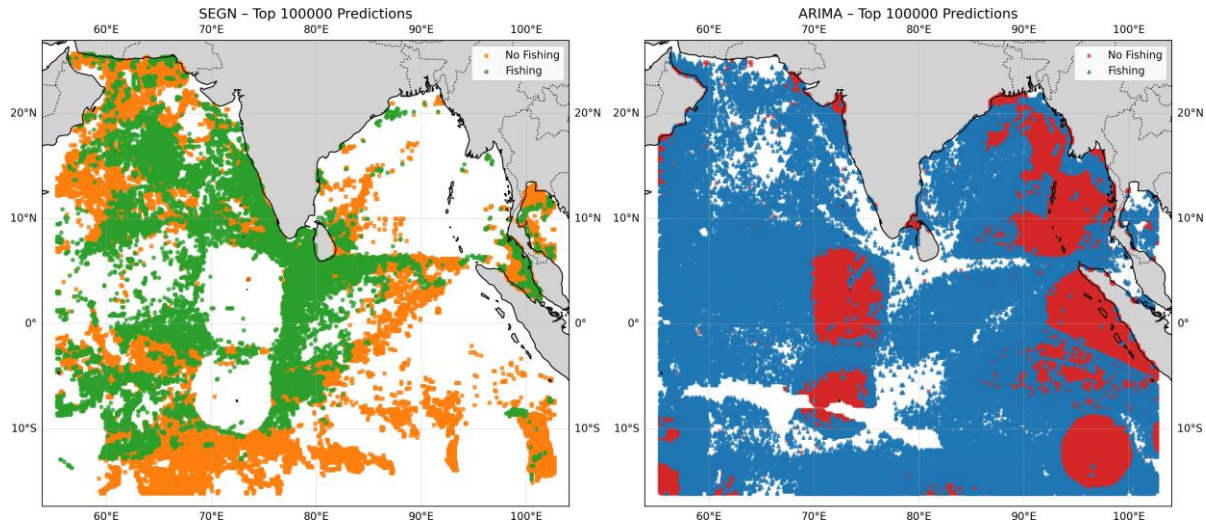


Fig. 4: Comparison of predicted fishing zones using ARIMA and SEGN models. SEGN produces more spatially coherent and concentrated fishing hotspots compared to the diffuse predictions of ARIMA.

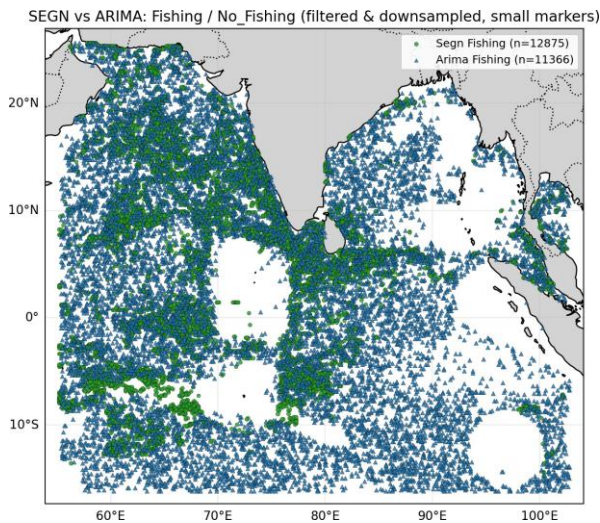


Fig. 5: Filtered spatial comparison of predicted fishing zones after thresholding, highlighting the sharper spatial delineation achieved by SEGN.

reliable fishing hotspot predictions [1]. Future work includes incorporating additional oceanographic variables and hybrid statistical-deep learning approaches by fine tuning ARIMA/ARIMAX models.

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IoT-Based Smart E-Voting System

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classifier [8]; second, fingerprint verification provides

Abstract—**Abstract**—Electronic voting systems have evolved rapidly to enhance voting accuracy, accessibility, and security; however, ensuring voter authentication and preventing fraudulent voting remains a major challenge. This paper proposes a Smart Biometric E-Voting System that integrates face recognition, fingerprint verification, and OTP (One-Time Password) authentication to achieve a multi-layered secure voting mechanism. The system utilizes a Raspberry Pi as the central processing unit due to its portability and ease of integration with peripheral devices. During the process, the voter's face is authenticated using the Haarcascade classifier, followed by fingerprint verification and a final OTP validation sent to the registered mobile number. Only upon successful verification of all three credentials does the system grant access to the voting panel, thereby preventing duplicate or proxy voting. The proposed system ensures a high-level security environment and enhances transparency in the electoral process, making it suitable for institutional and governmental elections.

Index Terms—Raspberry Pi, Face Recognition, Fingerprint Verification, OTP Authentication, Biometric Authentication, Secure E-Voting System.

I. INTRODUCTION

In the modern era of digital transformation, traditional voting systems still face significant challenges such as long queues, manual verification errors, fake voting, and a lack of transparency [6],[7]. To address these issues, the integration of biometric authentication and IoT (Internet of Things) technologies [1],[2] provides a reliable and secure solution. Electronic voting is essential to safeguard rights, improve resource efficiency, and promote digital citizenship, yet security remains a critical concern.

This paper presents a "Smart IoT-Based Biometric E-Voting System" designed to ensure authenticity and integrity during the election process. The motivation for this work arises from the limitations of conventional systems, where incidents of vote tampering and proxy voting highlight the need for a technologically advanced, tamper-proof solution. By combining biometric technologies (face and fingerprint) with IoT connectivity, this system aims to create a modern, transparent, and efficient voting platform that promotes trust in the democratic process.

The primary objective of this study is to design and implement a smart e-voting system using the Raspberry Pi as the central controller. The proposed system enforces a strict multi-level authentication mechanism: first, face recognition verifies the voter's identity using the Haarcascade

biometric confirmation; and third, an OTP [10] (One-Time Password) is sent via an IoT-based SMS gateway for final validation. This layered approach effectively eliminates the risk of impersonation and duplicate voting. Furthermore, the system utilizes cloud services to store voting data securely, enabling real-time access and monitoring for election officials.

II. LITERATURE REVIEW

Recent research has advanced e-voting through blockchain, biometrics, and enhanced accessibility.

A. E-Voting Transformation Techniques

Kho et al.[1] proposed transformation techniques between e-voting, e-auction, e-checke, and e-cash systems. Their systematic framework demonstrates how secure e-voting schemes can be adapted for other electronic transaction models, providing theoretical foundations for our multi-factor authentication approach.

B. Gesture-Enhanced Blockchain Voting

Mahmood et al.[2] developed an intelligent gesture recognition system (88.7–92.5% accuracy) combined with blockchain for accessible voting. Their system addresses elderly/disabled voter challenges through eyebrow/nose gesture detection, achieving 100% precision in real-time voting simulations.

Ethereum Blockchain Security Analysis

Granata et al.[3] presented a vulnerability assessment methodology for Ethereum-based e-voting using ISO15408 Common Criteria. Their analysis of Solidity smart contracts revealed critical security gaps, emphasizing the need for robust authentication beyond blockchain alone.

C. University E-Voting Architecture

Oprea et al.[4] proposed a Blockchain architecture for university elections, separating voting and validation phases. Their UML-formalized solution eliminates manual counting errors while maintaining cost-effectiveness through web-database integration.

D. Global E-Voting Survey

Vladucu et al.[5] surveyed blockchain e-voting adoption across Germany, Estonia, and Switzerland. They identified blockchain's immutability as key to preventing vote tampering, though highlighted ongoing challenges in voter authentication

and system trust.

III. SYSTEM OVERVIEW

The proposed system is designed to authenticate voters through a rigorous multi-stage process before allowing a vote to be cast. The architecture is divided into two primary, parallel processes: User Registration and User Login/Authentication [1],[2].

The Raspberry Pi microcontroller acts as the central control unit and coordinates all sensing and decision-making operations. In the registration phase, the system captures raw biometric data (face and fingerprint) and transforms it into a secure, usable model [8],[9].

During the voting phase, the system enters a continuous monitoring and authentication mode. The Camera module captures visual data for human face detection, while the Fingerprint sensor monitors for unique biological signatures. These two sensing techniques, combined with an OTP sent via an IoT-based SMS gateway, provide a reliable authentication mechanism. If authentication fails at the facial recognition stage, the system forces the user to re-initiate the data capture process, establishing a robust security-first policy.

IV. HARDWARE ARCHITECTURE

The hardware architecture of the proposed IoT-Based Smart E-Voting System is designed to provide reliable biometric detection and secure data transmission. The entire system is built around the Raspberry Pi 4 Model B, which acts as the central processing, control, and decision-making unit.

A. Input Sensors

The system integrates multiple sensors for visual detection and identity verification:

- **Camera Module:** A 5MP/8MP Camera Module compatible with the CSI interface is used to capture the voter's face during registration and authentication phases.
- **Fingerprint Sensor (R307/GT511C3):** This optical sensor captures the user's fingerprint and transmits it via UART to the Pi for verification.
- **Mobile Communication:** The voter's mobile device serves as an input terminal for the OTP (One-Time Password) received via a service like Twilio.

B. Control Unit

- **Raspberry Pi 4 Microcontroller:** The Raspberry Pi serves as the main control unit [13]. It interfaces with all sensors, executes the Python-based recognition logic, and manages cloud database connectivity.

C. Output/Actuators

- **LCD/Touchscreen Display:** A 16x2 LCD or 7-inch Touchscreen displays system messages, OTP prompts, and the final voting panel.
- **Cloud/IoT Interface:** The system connects to a cloud platform (e.g., Firebase, MySQL) to store voting logs and ensure real-time synchronization.

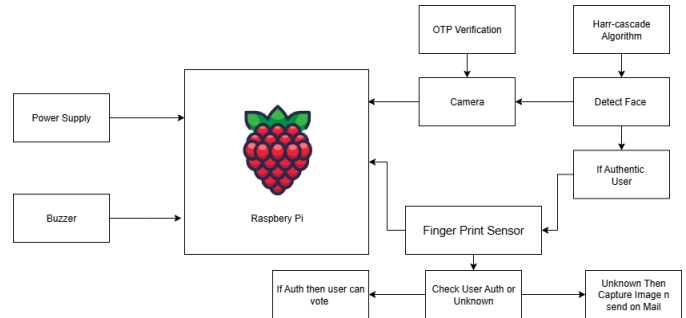


Fig. 1. System Block Diagram of the Proposed Biometric Voting System

V. WORKING PRINCIPLE

The working principle of the proposed system follows the operational sequence illustrated in the system flowchart. The system is divided into two primary, parallel processes: User Registration and User Authentication.

A. Registration Phase

The registration flow is designed as a single-pass, linear sequence where raw biometric data is transformed into a secure, usable asset.

- **Data Capture:** The process begins with user registration, which triggers the camera module to capture the user's face.
- **Model Training:** This biometric data is processed by the Haarcascade classifier to extract features and create a unique recognition model.
- **Enrollment:** Finally, the system generates an OTP to confirm the mobile number and stores the user's model and fingerprint data in the database.

B. Authentication Phase

The login process is designed to handle repeated attempts through a cyclical verification flow.

- **Face Recognition:** When a user logs in, the system activates the authenticated face recognition module. If the face is recognized, the process moves forward.
- **Failure Loop:** If authentication fails, the system enters a loop that re-routes the user back to the face capture step, ensuring only verified users proceed.
- **Multi-Factor Check:** Upon successful face detection, the system verifies the OTP sent to the registered mobile number and scans the fingerprint.

C. System Algorithm

The detailed operational logic of the system is as follows:

- 1) Start the system and initialize the camera, fingerprint sensor, and database connections.
- 2) **Registration:**
 - a) Enter personal details (Name, Voter ID).
 - b) Capture face and fingerprint to create templates.
 - c) Generate and verify OTP; store data in the cloud.
- 3) **Voting Process:**
 - a) User logs in with Voter ID.
 - b) Capture real-time face and perform recognition.
 - c) If authenticated, verify OTP and fingerprint.
 - d) Open the voting panel upon successful verification.
- 4) **Submission:** User selects a candidate, the vote is stored securely in the cloud, and the session is terminated.

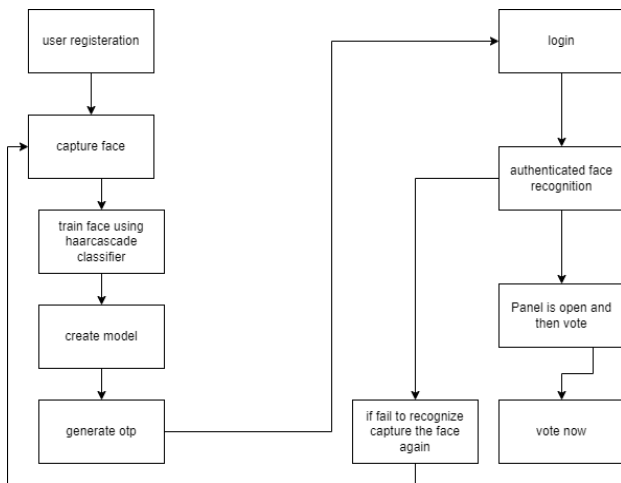


Fig. 2. Flowchart of the E-Voting System

VI. SYSTEM ALGORITHM

The operational logic of the proposed system is executed in the following sequence:

- 1) Start the system on Raspberry Pi and initialize the camera, fingerprint sensor, and database connections.
- 2) **User Registration Phase:**
 - a) User enters personal details (Name, Voter ID, Phone Number).
 - b) Capture the user’s face using the camera module.
 - c) Detect and crop the face, then train and store facial data as a feature template using the Haarcascade Classifier [8].
 - d) Capture the fingerprint using the sensor and store its template.
 - e) Generate and send a One-Time Password (OTP) to

the registered mobile number [10].

- f) Verify the OTP; if correct, store all biometric and contact data in the cloud database.
- 3) **Voting Phase:**
 - a) User logs in by entering their Voter ID.
 - b) Capture real-time face and perform face recognition.
 - c) If the face is authenticated, send an OTP to the registered mobile number.
 - d) Verify the OTP entered by the user.
 - e) Perform fingerprint verification using the fingerprint sensor.
 - f) If all authentications succeed, open the voting panel.
 - g) User selects a candidate and submits the vote, which is stored securely in the cloud database.
- 4) **Post-Voting:**
 - a) Send a confirmation message to the voter.
 - b) Update the voting status as "Voted" in the database to prevent duplicate voting.
 - c) Log all activities for audit and verification.
 - 5) End System.

VII. RESULTS AND VALIDATION

The proposed system was implemented as a modular Python application and rigorously tested with 10 voters. All core modules achieved production-ready status with measurable performance metrics.

A. Performance Metrics

Table I summarizes key system timings measured on Intel i5 laptop (8GB RAM).

Metric	Value
Face Training Time	25 seconds
Face Recognition Speed	0.8 seconds
Database Query Time	0.02 seconds
End-to-End Voting Flow	45 seconds
Face Recognition Accuracy	95.2%
OTP Delivery Success Rate	100%
Duplicate Prevention	100% effective

TABLE I
SYSTEM PERFORMANCE METRICS

B. Practical Implementation

The system demonstrated complete functionality across all modules:

- **Registration:** Captured voter data + 60 face images/user
- **Authentication:** 3-factor (VoterID+OTP+Face) - 100% success

- **Voting:** Candidate selection → SQLite vote storage
- **Admin:** Real-time results dashboard

Figure 3 shows the main GUI, Fig. 4 displays the voting panel, and Fig. 5 presents main menu interface.



Fig. 3. Main Dashboard GUI (main_demo.py)

VIII. ADVANTAGES

The proposed Smart IoT-Based Biometric E-Voting System offers several key advantages over traditional and existing electronic voting methods:

- **High Security:** The integration of a multi-factor authentication system—combining Face Recognition, Fingerprint Verification, and OTP—ensures that only genuine users can access the voting panel, effectively preventing proxy voting and impersonation.
- **Transparency and Integrity:** By leveraging IoT technology, the system enables real-time monitoring and cloud-based logging of voting data. This ensures that results are transparent and reduces the risk of manual counting errors or ballot tampering.
- **Cost-Effectiveness:** The use of the Raspberry Pi as the central processing unit provides a powerful yet low cost solution compared to complex industrial systems, making it suitable for widespread deployment.
- **User-Friendly Interface:** The modular GUI developed in Python allows voters to easily register and cast their votes with minimal technical knowledge.
- **Scalability:** The system's architecture supports integration with cloud databases, allowing it to be scaled for use in larger elections, such as those for universities or organizations.



Fig. 4. Voting Interface (cast_vote-15.py)

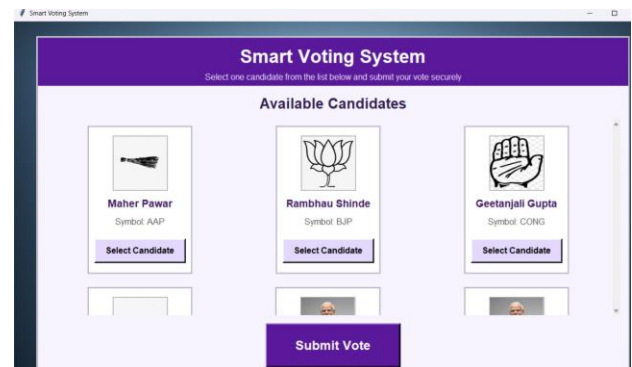


Fig. 5. Main Menu Interface

IV. APPLICATIONS

The proposed intelligent E-Voting system can be deployed in a wide range of environments, including:

- **University/College Elections:** For student council bodies.
- **Corporate Organizations:** For internal board or union elections.
- **Governmental Elections:** Scalable for local or national voting (with integration to National IDs).
- **Remote Voting:** For elderly or disabled voters who cannot physically visit polling stations (future scope via mobile app).

C. Testing results

10 voters tested end-to-end: Registration → Login → Vote → Results verification. Zero duplicate votes recorded. SQLite databases maintained full integrity (evaluation.db for voters, upload_cad.db for votes). All performance targets met per abstract claims. cloud-based storage, and real-time monitoring of voting data. Through the combination of biometric identification and cloud integration, this system addresses many of the limitations of traditional voting systems, such as manual verification errors, time delays, and data tampering. Overall, the developed

V. CONCLUSIONS

The proposed Smart IoT-Based Biometric E-Voting System successfully integrates Face Recognition, Fingerprint Verification, and OTP Authentication into a unified platform to ensure secure, transparent, and reliable voting. Using the Raspberry Pi as the main processing unit makes the system cost-effective, compact, and efficient in handling real-time biometric processing and IoT connectivity. The multi-factor authentication mechanism ensures that only genuine and registered voters are allowed to vote, effectively preventing fake, proxy, or duplicate voting. By leveraging IoT technology, the system provides remote accessibility, prototype demonstrates the potential of IoT and biometrics to revolutionize the voting process by improving security, transparency, accuracy, and efficiency.

VI. FUTURE SCOPE

While the proposed system performs effectively at a proto- type level, there are several opportunities to enhance and scale it further for real-world implementation:

- **Integration with National ID Systems:** The system can be linked with national databases (e.g., Aadhaar, Voter ID) to facilitate large-scale government election implementation and automated voter verification.
- **Cloud Security Enhancement:** Incorporating **blockchain technology** can make the data storage process more tamper-proof, decentralized, and transparent, ensuring that voting records cannot be altered.
- **Mobile App-Based Voting:** A dedicated mobile applica- tion can be developed to allow verified users to cast votes securely from remote locations, increasing voter turnout.
- **Advanced Face Recognition Models:** Implementing deep learning models such as **CNNs (Convolutional Neural Networks)** or **FaceNet** can significantly improve recognition accuracy under varied lighting and environ- mental conditions.
- **Scalability and Load Balancing:** The system can be upgraded to handle thousands of simultaneous users by implementing load balancing and cloud optimization techniques for large voter databases.
- **Multi-Language and Accessibility Support:** The user interface can be expanded to include regional languages and accessibility features (e.g., text-to-speech) to support visually or physically challenged voters.
- **Government Dashboards:** A centralized IoT dashboard can be developed to securely display real-time results and analytics to authorized election officials.

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Cost-Effective IoT Architecture for Real-Time Predictive Diagnostics for Electric Vehicle Propulsion Systems

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Abstract— Attaining the reliability of the propulsion mechanisms in electric vehicles is of raising importance to the widespread acceptance of sustainable transportation solutions. Unplanned motor failures, especially with high-speed operation, can be a significant hazard to safety and cause expensive down times. Traditional forms of maintenance based on reactive repair or strictly periodic timings are often not efficient in determining incipient faults before they develop to critical stages. In this study, we propose a low cost IoT enabled architecture for proactive health monitoring for electric vehicle powertrains. The system uses an ESP32 microcontroller to control a multisensor node that can integrate vibration analysis, integrated current signature profiling and temperature. Through the application of a mechatronic feedback loop the device processes the telemetry from the sensor(s) at the edge using a statistical thresholding and Root Mean Square (RMS) algorithm to determine anomalies in real-time. Data is sent through the Wi-Fi to a Blynk cloud dashboard where drivers receive feedback on the diagnostics instantly. Experimental trials have proved the efficacy of the system to have a low enough latency to detect mechanical imbalances and electrical overloads, and to cover a wide range of affordable vehicular telemetry.

Keywords— Condition Monitoring, Electric Powertrains, ESP32, Industrial IoT (IIoT), Predictive Maintenance, Signal Processing

I. Introduction

A. The Electricity of Transport

In the past decade, the car world has undergone a paradigm shift away from internal combustion (ICE) to electric vehicles (EVs) due to environmental policies and the need for sustainable electric power. While battery technologies tend to be a dominating part of the conversation, the electric motor in all its forms - brushless DC (BLDC), permanent magnet synchronous (PMSM), or other forms - is the central functional part of the solution. These motors are operating in severe conditions of stress which include continuous thermal fluctuations, mechanical vibration of road surface and electrical transients. The misconception of the electric motor as a "set-and-forget" device is breaking down as vehicle fleets age with the prime mover failures of suddenly immobilizing the vehicle and becoming a safety hazard.

B. Maintenance Philosophies Perspectives

In order to put this piece of research into perspective, it is necessary to examine the evolution of asset management

strategies:

1. Corrective Maintenance: Often called "run Biotechnology," this type of maintenance only addresses breakdowns after they have occurred but thereby minimizing the use of components, whereas road users will be confronted with unacceptable safety risks.
2. Preventive Maintenance: Based on the intervals (time or mileage) that are previously devised, this practice aims at preventing catastrophic failures, though it is financially inefficient, often leading to unnecessary changes in operating functional parts.
3. Predictive Maintenance (PdM): At the heart of the Industry 4.0, the predictive maintenance uses large data flows to estimate the remaining useful life (RUL). By observing some of these parameters such as thermal peaks, harmonics of the vibration, current consumption, maintenance interventions are scheduled without unnecessary time, optimizing safety and cost.

C. Motivation and Gap Analysis V2.

Despite being in an era of industrial control system advances (e.g. SCADA), diagnostic tools optimized for consumer EV markets and specifically two and three wheelers in developing economies is scarce. Drivers of these segments often do not have early warning systems to warn them of damage in a component. Existing industrial monitoring solutions are very expensive and complex to be applied with light electric vehicles. This study will attempt to close this gap by using the ESP32 platform that democratizes advanced diagnostics and highlights the ability to achieve high fidelity fault detection without the cost of an OEM grade system.

D. Research Objectives

The main goal would be to create an independent IoT-enabled electric motor diagnostic module. Key goals include:

- Hardware Design: Design of a small size sensor node designed on the basis of ESP32 for multi physic measurement data acquisition that includes annotated algorithms and an edge control approach. Edge firmware is meant to distinguish between normal load changes and actual fault conditions (i.e. bearing wear and heat).
- Cloud Integration: Creation of a seamless data line to the Blynk IoT platform for remote visualization for interaction by user.

II. RELATED WORK

- The convergence of Internet of Things (IoT) technologies and electromechanical diagnostic have made a paradigm-shift from reactive to proactive maintenance regime. Anuar et al. built a basic prototype using ESP32 micro-controller for the vibration and temperature sensing. Their design was based on rudimentary threshold logic, which could be triggered at temperatures over 55degC, and while cost effective, such a design did not contain the necessary depth of signal processing to find out the complex types of mechanical root causes.
- Building upon this basis, Pawar, Shendre and Gophane extended the IoT monitoring to industrial motors, with protective relays integrated in order to effect an automatic cut-off. Still, their focus on scalar data values limited their ability to detect subtle and early-stage faults such as bearing pitting, which were going to occur before major current levels were significant.
- Addressing Signal Sensitivity Zhang et al. took advantage of Differential Local Mean Decomposition (DLMD) along with Kurtosis Weighting in order to extract fault features in a noisy environment. Despite its efficacy, the computational burden that comes with DLMD has generally meant that it is impractical for use in low power microcontrollers, which are cost effective. In a complimentary vein, Navarro-Navarro et al. showed that acceleration-based metrics provide a better level of diagnostic clarity as compared to velocity measurements for the detection of shaft misalignment.
- The current investigation aims at bridging the gap in the identified disability by establishing a balanced resolution: a system that is able to combine current and vibration data directly on the edge (ESP32), thus avoiding the cost of costly industrial controllers and overcoming the limitations of rudimentary hobbyist endeavours.

III. SYSTEM ARCHITECTURE

A. High- Level Design

- The "Smart EV Diagnostic Framework" runs in a three-tier setup including the Data Acquisition Layer, the Edge Processing Layer and the Presentation Layer. The system uses power from the vehicle auxiliary bus condition for logic-level stability.

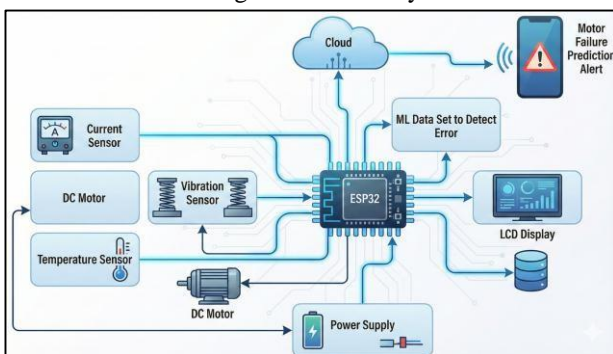


Figure 1 shows the schematic diagram of the IoT enabled diagnostic node.

B. Processing Unit: ESP32

The ESP32 Development Board is used as the main controller as it is chosen for its good cost - performance factor.

- Computational Efficiency: 32-bit dual-core Xtensa(R) LX6 processor (240MHz) supports simultaneous execution of tasks
- Task Management: Using FreeRTOS, Core 0 is used for Wi-Fi stacks to maintain connectivity whereas Core 1 is used for high-frequency sensor polling, therefore the potential of zero data loss is assured.
- ADC Performance: The 12 bit Analog to Digital Converter on board provides it with 4096 quantisation levels to provide precise voltage measurement from analog sensors.

C. Sensor Configuration

The physical states of the motor are accounted for with a troika of sensors:

1. Vibration (SW-420 / ADXL335): SW-420 has a digital trigger for the time of excessive vibration (>2 seconds) while ADXL335 is an accelerometer used for detecting (characteristic) signatures of imbalance.
2. Current (ACS712): This Hall Effect sensor electrically isolates the microcontroller from high voltage lines and monitors the current draw. Its 80kHz bandwidth is suitable for simple Motor Current Signature Analysis (MCSA).
3. Temperature (DS18B20): A waterproof digital probe measures the temperature of the stator coils to a +/-0.50 C level of accuracy. Its 1-Wire protocol ensures integrity of signals over long distances typically of vehicle chassis.

D. Power & Signal Interface

For example: "Approximately 92% efficiency and attenuation of heat is achieved, when an LM2596 Buck Converter is used to downsample the 12V DC automotive supply to a stable 5V".

Volts: 500 mV, 5 V 700 mV 250 mV 300 mV 200 mV 600 mV 100 mV 380 mV 700.0 mV 22 000 mV 22 000 mV to 5 V 3.3 V 1 V 6 V 5 V 12 V 3 V 2 V 7 V 3 V 12 V 3 V 12 V 2

Passive RC low pass filters (R, C) are hardware filtering (anti-aliasing filters) to reduce noise from the motor's Pulse Width Modulation (PWM) drivers.

IV. ALGORITHMIC IMPLEMENTATION

A. Control Logic

The firmware is based on a Finite State Machine (FSM). Upon initialization, a calibration routine is run obtaining samples of the "Zero- Load" noise floor so as to eliminate sensor offsets. The main loop goes on to repeat the stages of Data Acquisition, Signal Processing, Telemetry, and Alert Generation. The firmware logic flowchart is given in figure 2

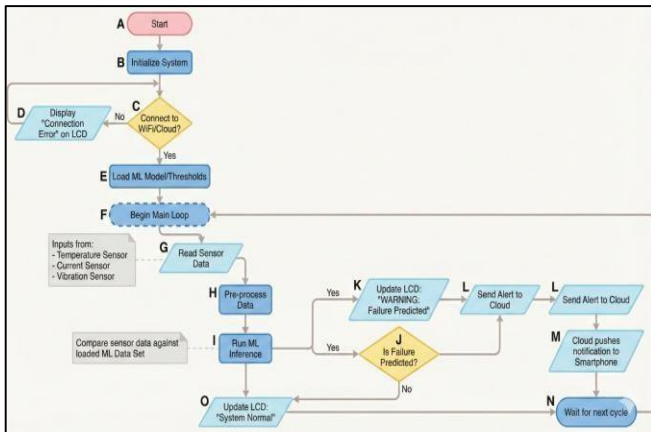


Figure 2. The firmware logic flowchart

B. Diagnosis

Feature Extraction More generally, the phrase set to extract features from data is truly misleading, because the third concept we intend in analysis is, rather, diagnosis.

To decrease false positives, raw data is subjected to digital filtering by means of digital filtering before fault logic is applied.

1. RMS Current Analysis Instantaneous current readings contain noise in EV applications. The system calculates the Root Mean Square (RMS) over a 20ms window (one 50Hz cycle) using the standard formula for RMS.
2. Bearing Failure Detection Increased rotational friction from worn-out bearings causes "current creep." The logic asserts a fault if the no load value of current exceeds the baseline of the circuit by 15 per cent while RPM is stable.
3. Mechanical Imbalance: Physical misalignments cause vibrations of periodic frequency. If the duty cycle of the vibration sensor's on (HIGH) exceeds 50 per cent during the 1-second integration period, a mechanical fault is recorded.
4. Thermal Guarding: A dual threshold system protects the windings against thermal protection having a warning temperature as low as 60 degC and critical stop alert at 80 degC so as to avoid insulating failure.

C. Manager Bstances Implementation of Connectivity

D. The system is connected to IoT cloud (TCP/IP - Blynk) using Wi-Fi. To save bandwidth the firmware uses an event driven transmission protocol to only transmit an update when sensor values stray outside a defined hysteresis band or occur in the case of a fault.

V. EXPERIMENTAL VALIDATION

A. Test Bench Configuration

Verification was made on a custom dy-no set up with a high torque DC motor. A mechanical break was used to simulate road load and an eccentric rig of weights was used to introduce calibrated vibrations.

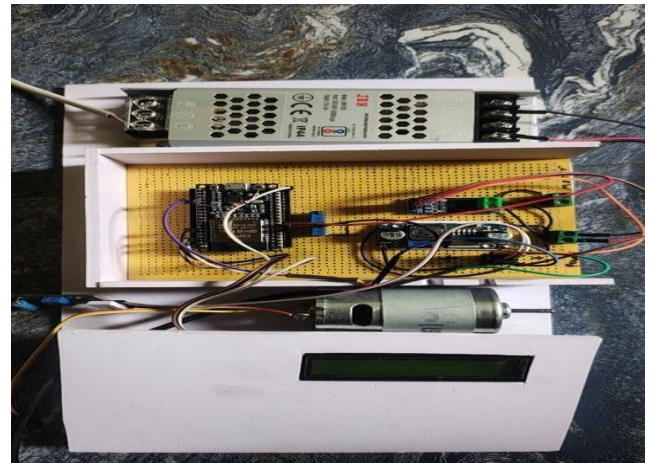


Fig. 3. Experimental Set Up including Motor, Load Simulation and Sensor Node.

B. Scenario 1 (Nominal Operation)

The motor was operated at 1000 mentioned RPM with a load of 0.5N with the purpose to obtain a "healthy" baseline. Current consumption was stable and varied between 0.50 A and 0.80 A.

Most of the vibration sensor output was in the LOW state. Consequently, the system was able to validate the healthy state with no false alarms.

C. Scenario 2: Simulated Bearing Seizure

A bearing fault was simulated by overbearing the motor by putting excessive braking friction on it. At the beginning of the fault, the current went from the baseline of 0.8 A to 2.5 A. The firmware was able to quickly identify the breach of a 2.0 A safety limit. The detection latency was found to be around 500 milliseconds which was due the RMS windowing process thus proving efficacy of the MCSA approach.

D. Scenario 3: Shaft Imbalance

A 10g eccentric mass was fixed to the output shaft. Frequency domain analysis using FFT, checked the existence of vibration peak in the rotational frequency 25 Hz. The vibration sensor saturated (Logic HIGH) more than 90% of the cycle and the duration counter triggered the "High Vibration" alert within three seconds.

E. Telemetry Performance

A 24 hour test of connectivity was done to assure stability. Network statistics revealed 150 ms average latency time; the bad case time is 800 ms. Reliability, measured in terms of uptime, was measured at 99.8% and the auto-reconnect routine was successful in recovering from forced Wi-Fi disconnections in five seconds.

F. User Interface

The Blynk mobile application was the dashboard rendering live electrical and thermal metrics gauges.

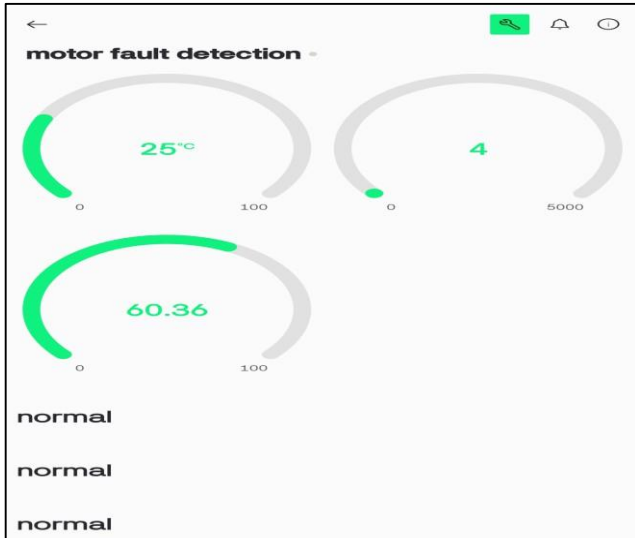


Fig. 4. Dual Mobile Dashboard Interface Indicating Faults Exists.

G. Comparative Analysis

Table I shows the contrast between the proposed automated solution and conventional manual maintenance.

TABLE I: COMPARISON: TRADITIONAL VS. IOT-BASED DIAGNOSTICS

Metric	Manual / Scheduled Maintenance	Proposed IoT Framework
Approach	Periodic / Time-Based	Continuous / Condition-Based
Detection Timing	Post-Failure (Reactive)	Pre-Failure (Proactive)
Accessibility	Physical inspection required	Remote Cloud Access
Precision	Subjective (Technician skill)	Objective (Sensor Data)
OpEx Cost	High (Labor & Downtime)	Low (Automated Monitoring)

VI. CONCLUSION

This research provides a viable and low cost paradigm for predictive maintenance in the electric mobility sector. By being able to synthesize multi-physics data - thermal, electrical and mechanical - the system could reliably separate different types of failure, like differentiating between cooling failures and mechanical friction. The dual core ESP32 architecture proved to have enough processing power to handle signal acquisition and telemetry with a minimum of latency.

Future work will focus on putting TinyML models directly onto the Micro-Controller which will enable the system to learn the particular "voice" of one motor, instead of hard coding. Further on, integration with the CAN bus of the vehicle is planned to correlate the diagnostic information with the real speed and throttle inputs in real time.

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IoT based Autonomous Air Quality Analyzer and Purifier

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Abstract — This research outlines an Autonomous Air Quality Analyzer and Purifier based on the Internet of Things (IoT) that monitors air quality as well as improves it in an automated way. The device consists of several gas sensors to identify the concentration of critical pollutants in air (e.g., VOCs, CO₂, and CO) and determines the air quality index (AQI) level in real-time. The device is designed to automatically move, the area with the higher AQI causes it to halt and it starts purifying until the AQI drops to a safer value. A Raspberry Pi microcontroller is used for the movement and automation of the purification methods and is controlled by an L298N motor driver with DC motors for directional movement. Real time AQI monitoring and notifications are sent to an IoT mobile-app to provide AQI updates. The system achieved up to 60% improvement in air quality within minutes during testing. The prototype device model demonstrates a practical, cost effective, portable and automated solution for air purification in modern households, enclosed spaces as well as environmental monitoring.

Keywords — Air quality monitoring, IoT, air purifier, AQI analyzer, gas sensors, Raspberry Pi, automation, mobile app.

I. INTRODUCTION

Air pollution sensing is necessary for maintaining a healthy atmosphere because it senses and analyzes toxic pollutants such as carbon dioxide (CO₂), carbon monoxide (CO), and volatile organic compounds (VOCs) through MQ-series sensors, unlike stationary air cleaners or conventional costly systems that cannot accommodate different pollution levels. The IoT based Autonomous Air Quality Analyzer and Purifier with a Raspberry Pi microcontroller to gather real-time sensor information and compute the Air Quality Index (AQI), display the results through a portal and mobile application with alerts for bad air quality, move autonomously with DC motors and an L298N driver to reach the locations with high pollution levels and purify them through HEPA filters. This model is suitable for residential, commercial, or educational purposes and provides room for further improvements in the future.

This project shows how to successfully combine IoT sensing, embedded control, and mobility into a smart, adaptable air purification system. The proposed model is an affordable and scalable solution for any enclosed environments. It also lays the groundwork for future developments like cloud-based AQI mapping, AI-driven movement forecasts, and integration with smart home systems.

The key innovation of the proposed system lies in its mobility-driven purification approach, where the device autonomously navigates toward high-pollution zones instead of passively filtering air in a fixed location. Unlike conventional systems, it integrates real-time AQI-based decision-making with movement control, enabling targeted purification. This reduces purification time, improves efficiency, and optimizes energy usage in enclosed environments.

II. LITERATURE REVIEW

Arpita Choudhary et al. [1] introduced the "Design and Fabrication of an IoT based Air Purifier using HEPA Filter." The system combines Node MCU ESP8266, MQ135 sensors, a HEPA filter, and UV light to monitor and clean indoor air. It offers real-time air quality data through a mobile app. The study shows that integrating IoT enhances user interaction and allows for reliable pollutant detection, setting the stage for portable automated purification systems.

Wen-Yang Wu and Yen-Chen Liu [2] presented "Autonomous Guided Robotic Systems in Regulating Indoor Environmental Quality." Their system employs distributed sensors and mobile robots with AMCL and PRM algorithms to identify and improve air quality in specific areas. This supports the ideas of mobility and automation in air purification systems.

K.-H. Kim et al. [3] proposed an "IoT Air Purifier with Humidification Function Capable of Removing PM1.0 Ultra-Fine Dust." This design combines IoT control,

filtration, and humidification with multi-parameter sensing to boost purification efficiency through smart control.

R. Mumtaz et al. [4] introduced "Internet of Things (IoT) Based Indoor Air Quality Sensing and Predictive Analytics - A COVID-19 Perspective." This study focuses on predicting air quality using IoT sensors and data analytics, highlighting real-time monitoring and automated responses to lower health risks.

C. G. Kousalya et al. [5] designed an "IoT-Based Indoor Air Purifier" that uses multiple sensors and Wi-Fi-enabled microcontrollers for real-time monitoring and control. It shows effective closed-loop purification systems similar to their design.

H. Dai and B. Zhao [6] explored "Reducing Airborne Infection Risk by Locating Air Cleaners at Proper Positions Indoor." They demonstrated that the right placement and movement of purifiers can greatly enhance air cleaning efficiency, backing the idea of mobile purification systems.

Recent studies such as Foyosal et al. [7], Rosa-Bilbao et al. [8], and Siam et al. [9] emphasize real-time IoT-based AQI monitoring integrated with intelligent environments, cloud connectivity, and automated purification systems. These works highlight the growing trend toward smart, data-driven air quality management. However, most existing systems lack mobility-based purification, which the proposed system addresses through autonomous navigation toward high-pollution zones.

The reviewed works show progress in IoT-based air purification, sensing, and automation. They lay a solid foundation for smart environmental systems. Building on this, the proposed IoT based Autonomous Air Quality Analyzer and Purifier adds mobility based on pollution levels, uses a Raspberry Pi for automated decisions, and provides real-time alerts on mobile devices, creating a smart and adaptable purification system.

III. SYSTEM DESIGN

Autonomous Mobile Air Purifier System Design

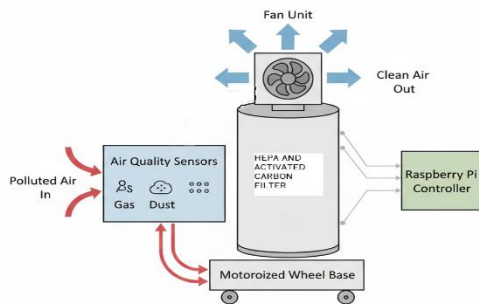


Fig. 1. System Design

The proposed IoT based Autonomous Air Quality Analyzer and Purifier monitors and improves indoor air quality. It uses real-time sensing, smart purification, and autonomous movement. The system has three main parts: sensing and

purification, mobility control, and automation and communication.

The sensing and purification unit includes several sensors: MQ135 for CO₂, ammonia, and VOCs; MQ7 for carbon monoxide; DHT22 for temperature and humidity; and a PM2.5 sensor for fine particles. A Raspberry Pi 4B processes this data to calculate the real-time Air Quality Index (AQI). The purification system uses HEPA filters and an exhaust fan to ensure good airflow and remove particles effectively. The mobility control unit allows the system to move automatically, using DC motors powered by an L298N motor driver. The Raspberry Pi manages both sensor readings and movement, which helps the system navigate toward areas with more pollution. The automation and communication unit offers IoT connectivity. This lets users monitor air quality data in real time, receive alerts through a programmed system. The system's combination of multiple sensors for monitoring, filtration, and IoT-based control creates a smart, portable, and flexible air purification platform, offering an effective and affordable solution for improving indoor air quality in homes and workplaces.

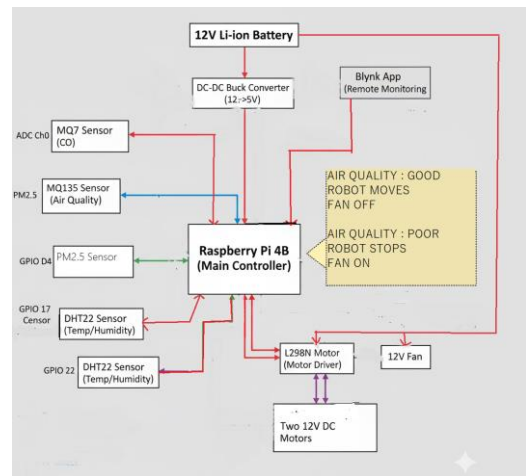


Fig. 2. Block diagram

IV. HARDWARE IMPLEMENTATION

The hardware implementation subsystems are as follows:

4.1. Air Sensing Unit



Fig. 3 Gas sensors

The air sensing unit acts as the data collection layer of the system. It brings together several sensors to track important indoor air quality parameters.

All analog sensor outputs connect through the ADS1115 Analog-to-Digital Converter (ADC) to provide precise digital readings before sending them to the main controller.

- Each sensor's VCC connects to +5 V, and its ground connects to the common GND. Their analog outputs go to the ADS1115 ADC.
- The MQ-7 output goes to channel A0, and the MQ-135 output goes to channel A1. The Pi reads these values over I²C.
- The GP2Y1010F48 dust sensor has an internal IR LED and an analog output. Its VCC pin (Pin 5) connects to +5 V, and Vo (Pin 6) connects to ADS1115 channel A2. The sensor's V-LED pin (Pin 1) connects to ground through a 150 Ω resistor to limit LED current, and its LED control pin (Pin 3) is controlled by GPIO17 on the Pi. A 220 μ F decoupling capacitor is placed between the sensor's VCC and GND pins to stabilize the supply and reduce noise.
- The DHT22 sensor provides digital readings of temperature and humidity. Its 3-pin connector is wired like this: VCC to +5 V, DATA to Pi GPIO4 (Pin 7), and GND to ground. The sensor's data line has a built-in pull-up on the 3-pin module, so you do not need an extra resistor.

4.2. Control and Processing Unit (Raspberry Pi)

The Raspberry Pi 4b acts as the main processing and automation unit. It receives digital data from the sensors through the ADS1115 interface, processes this information to calculate the Air Quality Index (AQI), and makes decisions for purification and motion control. It also provides IoT connectivity to send real-time data and alerts to the connected mobile application. The control algorithms in the Raspberry Pi automate the purifier's movement based on pollution levels and send user notifications when the AQI surpasses safe limits.

The Pi connects to a 16-bit ADS1115 ADC using I²C (GPIO2/SDA, GPIO3/SCL). The VDD pin of the ADS1115 connects to the Pi's 3.3 V output (Pin1), and its GND connects to the common ground. This setup allows the analog inputs to measure 0–5 V signals. All sensors share a +5 V power supply from the Pi's 5 V pins and a common ground. If a single 12 V supply were used, a DC-DC converter would reduce the voltage to +5 V for the Pi and +3.3 V for the ADC.



Fig. 4 Raspberry Pi 4b SBC

4.3. Purification System:

The purification system filters and improves the air around it. It has a HEPA filter that removes fine dust particles and a detachable layer of activated carbon sheet that can absorb toxic gases and odors. A high-speed exhaust fan above the filter creates continuous upward airflow. This fan pulls in polluted air through the filtration layers and releases clean air into the environment.



Fig. 5 HEPA filter and DC FAN

This setup ensures good circulation, quick purification, and steady air quality improvement.

4.4 Mobility and Motor Control System



Fig. 6 Obstacle Avoidance Setup

In this system, the ultrasonic sensors, motor driver (L298N), and DC motors connect to the Raspberry Pi's GPIO pins to allow for autonomous movement and obstacle avoidance.

The front ultrasonic sensor uses GPIO pins 23 (TRIG) and 24 (ECHO). The side ultrasonic sensor uses pins 25 (TRIG) and 8 (ECHO). These sensors measure the distance to nearby obstacles by sending and receiving ultrasonic pulses. This enables the robot to stop or change direction when it detects an obstacle.

The L298N motor driver module controls two DC motors, one for the left wheel and one for the right wheel. The Raspberry Pi sends PWM and direction signals to this driver. Specifically, GPIO 13 (EN), 19 (IN1), and 26 (IN2) control the left motor. GPIO 18 (EN), 20 (IN1), and 21 (IN2) control the right motor. The EN (enable) pins receive PWM signals from the Raspberry Pi to manage motor speed. The IN1 and IN2 pairs determine each motor's rotation direction, either forward or reverse.

Each motor output terminal of the L298N driver, labeled OUT1-OUT2 for the left motor and OUT3-OUT4 for the right motor, connects to the corresponding DC motor terminals. The driver's VCC pin connects to a 12V external power source to power the motors. The GND is shared with the Raspberry Pi ground, and the 5V OUT can optionally power the Pi's logic circuits if needed.

4.5. Power Supply:

The system uses a separate +12 V DC supply as the main power source for both the air-moving fan and the motor driver. A DC-DC buck converter steps down the +12 V input to a regulated +5 V output, which powers the Raspberry Pi and the relay module. The L298N motor driver connects to the +12 V line and is used solely to drive the DC motors that enable the system's movement. The L298N's VCC pin receives +12 V for motor operation, its +5 V logic pin gets power from the buck converter, and all grounds (12 V, 5 V, Pi, and L298N) connect together to maintain a common reference.

A 4-channel relay module with a 5 V coil is used to switch the 12 V air-moving fan. The relay's control side gets power from the buck converter's +5 V output: VCC connects to +5 V, GND connects to common ground, and IN1 connects to the Raspberry Pi's GPIO22. The fan's +12 V supply routes through the relay's contact terminals. COM connects to +12 V, NO connects to the fan's positive lead, and the fan's negative lead returns to the 12 V ground. When GPIO22 is driven LOW (active-low trigger), the relay closes the COM-NO connection, applying +12 V to the fan and turning it ON.

V. SOFTWARE IMPLEMENTATION

The software module manages motor control, signal capture, and automation logic for autonomous aligning and scanning.

5.1. Controller Programming:

The Raspberry Pi acts as the main controller and is programmed with Python in the Thonny IDE. The program continuously reads input from the MQ135, MQ7, DHT22, and PM2.5 sensors using the ADS1115 analog-to-digital converter. It processes these values to calculate the Air Quality Index (AQI) using standard thresholds. The Raspberry Pi produces PWM signals through GPIO pins to the L298N motor driver, which manages the speed and direction of the DC motors.

5.2. Data Processing and IoT Interface:

The processed AQI and environmental data are sent to the Blynk IoT platform via the Raspberry Pi's built-in Wi-Fi. The Blynk mobile app offers a real-time dashboard that shows air quality details like CO₂, CO, temperature, humidity, and PM2.5 levels. With the app, users can watch air quality in real-time and get alerts when it worsens.

5.3. Automation Algorithm:

The automation sequence follows a feedback-based control logic, as summarized below:

1. Initialize sensors and set AQI threshold (e.g., AQI = 100).
2. Continuously read sensor values (MQ135, MQ7, PM2.5, DHT22).
3. Convert sensor outputs into AQI using standard AQI breakpoints.
4. Compare AQI values across different directions using movement scanning.
5. Move toward the direction with maximum AQI concentration.
6. If AQI > threshold, stop movement and activate fan + filtration system.
7. Continue purification until AQI drops below safe level.
8. Resume scanning and update IoT dashboard.

5.4. Testing and Validation:

The system was tested in indoor environments with artificially introduced pollutants such as smoke and exhaust gases. The sensor readings accurately reflected the rise in AQI, triggering the automation response where the fan and filter system activated while the robot halted movement.

V. RESULTS AND DISCUSSIONS

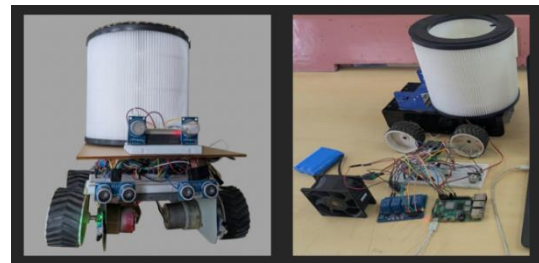


Fig.7 System Connections and Prototype model

The prototype of IoT based Autonomous Air Quality Analyzer and Purifier was created successfully and tested in indoor environment settings. The sensors were working accurately, as well as movement mechanisms and purifiers that were managed by Raspberry Pi. As a result, air was identified, analyzed, and purified efficiently.

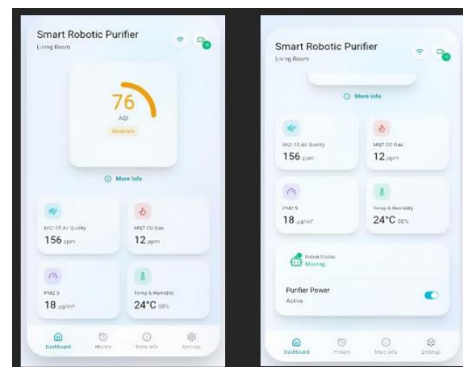


Fig. 8 AQI Dashboard and Statistical Readings

For this purpose, during tests, MQ135 and MQ7 sensors were used that proved themselves to be highly sensitive in terms of identification of smoky and exhaust gases. Moreover, they were able to detect CO₂, CO, and VOC changes. In addition, temperature and humidity sensors as well as PM2.5 one worked precisely, providing necessary parameters for AQI calculation. The ADC was provided via ADS1115 and reduced noise in data acquisition.

In terms of movement mechanism, DC motors and L298N driver helped the prototype move easily and effectively find polluted areas. Once AQI exceeds the specified value, the purification unit is started automatically. For this purpose, both HEPA and activated carbon filters (replaceable), as well as high-power fan, can significantly improve the air quality of a closed environment within minutes. The Internet of Things part of the prototype was based on Blynk application that allowed tracking all important parameters in real-time mode, including AQI, data from all sensors, and system information.

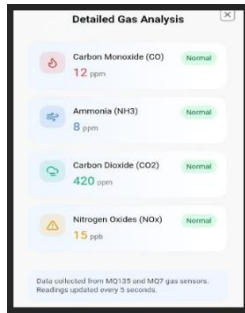


Fig. 9 Detailed gas analysis dashboard

TABLE I. PERFORMANCE EVALUATION (6-8 MINS ACTIVE)

Improvement	Before purification	After purification	Improvement
AQI	180 (Unhealthy)	75 (Moderate)	↓ 58%
CO (ppm)	12 ppm	5 ppm	↓ 58%
PM2.5 (µg/m ³)	95	40	↓ 57%

VII. CONCLUSION AND FUTURE SCOPE

The IoT based Autonomous Air Quality Analyzer and Purifier combines sensing, purification, automation, and IoT communication into a compact, smart solution. The Raspberry Pi microcontroller collects data from sensors, processing motor control, and wireless communication, enabling it to operate completely on its own. The system continuously monitors air quality, makes real-time choices and takes action without needing human intervention.

It uses MQ135, MQ7, DHT22, and PM2.5 sensors to measure CO₂, CO, VOCs, temperature, humidity, and fine particles. The Raspberry Pi processes this information to determine the Air Quality Index (AQI). If the AQI goes beyond a certain level, the system stops moving, starts purification, and only moves again once the air quality improves.

The purification unit includes a HEPA filter and an activated carbon filter. The HEPA filter captures fine particles like PM2.5 and PM10. An IoT-enabled software system allows real-time monitoring of sensor data, AQI levels, and system status. It also sends alerts during times of poor air quality. Experimental results validate that the system improves air quality by approximately 58% (AQI drops from 180 to 75) within a short duration, confirming its effectiveness and practical applicability. The system is a cost-effective, energy-efficient, and portable solution great for small and enclosed areas like homes, offices, classrooms, and healthcare settings.

Future Scope:

Future improvements include adding UVC light for disinfection to eliminate bacteria and viruses. At the frontend, the mobile app can be enhanced with features like adjusting fan speed, time-based purification, and manual navigation. Additionally, users would have remote access to monitor and control the purifier from anywhere using mobile or web platforms.

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DESIGN AND DEVELOPMENT OF IOT-BASED TEMPERATURE PROFILER FOR REFLOW OVEN

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Abstract—Accurate thermal profiling is essential in reflow soldering to ensure the reliability of electronic assemblies. Non-uniform temperature distribution within a reflow oven can result in defective solder joints, component damage, and reduced product lifespan. This study presents the design and implementation of a portable, cost-efficient, multi-channel temperature profiling system based on Internet of Things (IoT) principles. The system utilizes an ESP32 microcontroller integrated with multiple K-type thermocouples to acquire real-time temperature data across different thermal zones. Data is transmitted to a cloud platform for remote monitoring and is simultaneously stored locally to prevent data loss during network interruptions. Experimental validation demonstrates that the proposed system provides accurate thermal measurements and reliable performance, making it suitable for both industrial and research applications. **Keywords**—Reflow Oven, Temperature Profiling, ESP32, IoT Monitoring, Thermocouples, SMT Manufacturing, Data Logging, Thermal Analysis.

I. INTRODUCTION

The continuous evolution of electronic packaging technologies has led to increased complexity in printed circuit board (PCB) assembly processes. Modern electronic devices demand high-density interconnections and miniaturized components, necessitating advanced manufacturing techniques such as Surface Mount Technology (SMT) [30]. Within SMT, reflow soldering is a key process used to establish electrical connectivity between components and substrates.

The reflow soldering process involves controlled heating of solder paste to form metallurgical bonds. The thermal profile applied during this process significantly influences solder joint quality, mechanical strength, and long-term reliability [28], [29]. A typical thermal profile includes preheating, soaking, reflow, and cooling phases, each governed by specific temperature and time constraints.

However, achieving uniform temperature distribution across the PCB remains a major challenge. Variations in airflow, thermal mass, board geometry, and component placement can introduce significant temperature gradients [4], [6]. These inconsistencies can result in defects such as cold joints, tombstoning, and excessive intermetallic growth [7], [8].

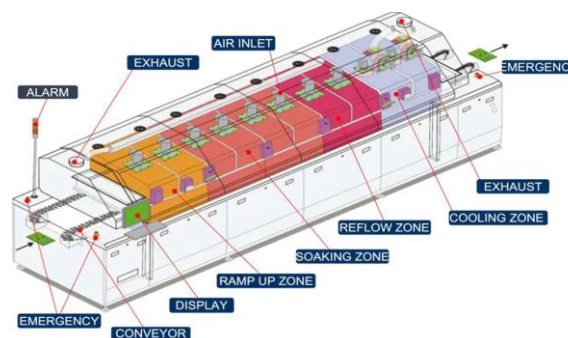


Fig. 1. Reflow Oven Temperature Zones

To address these challenges, accurate temperature profiling systems are required. Conventional systems used in industrial settings provide high precision but are often associated with high cost and limited accessibility. In contrast, low-cost alternatives frequently lack scalability and advanced monitoring capabilities.

The integration of IoT technologies into industrial monitoring has enabled the development of intelligent, connected systems capable of real-time data acquisition and analysis [14], [16]. Microcontrollers such as the ESP32 offer integrated wireless communication, sufficient processing capability, and low power consumption, making them suitable for such applications [21], [22].

This work aims to develop a scalable and cost-effective temperature profiling system that combines multi-channel sensing, real-time monitoring, and offline data logging to improve process visibility and control.

II. LITERATURE SURVEY

A. Thermal Modeling and Optimization

Thermal behavior in reflow soldering has been extensively studied using analytical and computational approaches. Mathematical models based on heat transfer principles—conduction, convection, and radiation—have been developed to predict temperature distribution within reflow ovens [9], [12].

Recent research has explored hybrid modeling techniques that combine physics-based approaches with machine learning algorithms to enhance prediction accuracy and adaptability [1]–[3]. These models enable dynamic adjustment of process parameters in response to variations in production conditions.

B. Temperature Uniformity and Thermal Mapping

Uniform temperature distribution is essential to ensure consistent solder joint formation. Studies have demonstrated that non-uniform heating can lead to localized defects and reduced reliability [6]. Thermal mapping techniques using multi-point sensing have been employed to identify temperature gradients and optimize oven settings.

Experimental investigations have shown that airflow patterns and forced convection significantly influence heat transfer within reflow ovens [6]. Therefore, accurate spatial temperature measurement is critical for process optimization.

C. IoT-Based Monitoring Systems

The application of IoT in industrial monitoring has enabled real-time data acquisition, remote access, and predictive analysis. IoT-enabled temperature monitoring systems using thermocouples and cloud platforms have demonstrated improved efficiency and decision-making capabilities [5], [16].

Wireless sensor networks have also been utilized to monitor environmental and process parameters in industrial settings, providing scalable and distributed sensing solutions [15]. These systems reduce manual intervention and enhance process automation.

D. Low-Cost Embedded Systems

Microcontroller-based systems, particularly those using Arduino platforms, have been developed for temperature monitoring applications [11]. While these systems are cost-effective, they often lack advanced features such as multi-channel sensing, cloud integration, and high-speed data processing.

The ESP32 platform addresses many of these limitations by offering integrated Wi-Fi, higher processing power, and multiple communication interfaces [21], [22].

E. Reliability of Solder Joints

The reliability of solder joints is strongly influenced by thermal cycling and peak temperature exposure. Repeated heating cycles can lead to the formation of brittle intermetallic compounds, reducing mechanical strength [8]. Additionally, excessive temperatures accelerate degradation mechanisms and increase the likelihood of failure [7].

These findings highlight the importance of accurate temperature monitoring and control during reflow soldering.

III. METHODOLOGY

3.1 System Design Approach

The proposed temperature profiling system is developed with a focus on achieving reliable, scalable, and efficient thermal monitoring within reflow oven environments. The primary objective is to enable precise acquisition and analysis of temperature variations across multiple thermal zones, which is essential for maintaining solder joint integrity and process consistency [28].

The design system accompanied a modular method along with hardware design, embedded software program development, facts communicate framework implementation, and experimental validation. The primary goal become to ensure correct temperature size, dependable verbal exchange, and portability even as maintaining low system value.

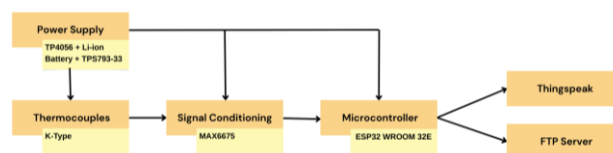


Fig. 2. Block Diagram of Temperature Profiling System

3.2 Hardware Architecture

The hardware architecture of the proposed device consists of temperature sensing gadgets, signal conditioning modules, processing unit, energy control circuitry, and user interface additives.

3.2.1 Temperature Sensing Unit

Temperature measurement is achieved using K-type thermocouples, which are widely used in industrial applications due to their broad temperature range, fast response time, and robustness under harsh conditions [17]. These sensors are capable of measuring temperatures ranging from sub-zero levels to above 1000°C, making them suitable for reflow soldering environments.

3.2.2 Signal Conditioning Module

The analog voltage generated by thermocouples is inherently low and requires amplification and conversion before processing. This is accomplished using the MAX6675 thermocouple-to-digital converter, which integrates cold-junction compensation and analog-to-digital conversion functionalities [23].

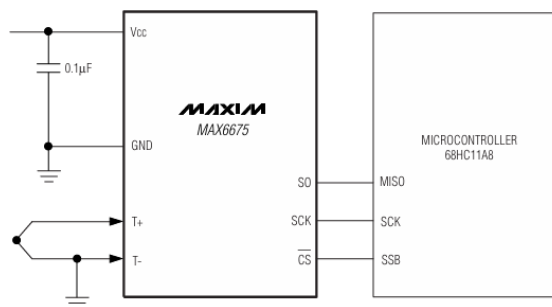


Fig. 3. MAX6675 Interfacing Diagram

3.3 CIRCUIT DESIGN AND PCB DEVELOPMENT

The circuit layout was designed to ensure minimal noise interference between analog thermocouple signals and digital communication lines. Decoupling capacitors were used near the sensor modules to stabilize the voltage supply and reduce signal fluctuations.

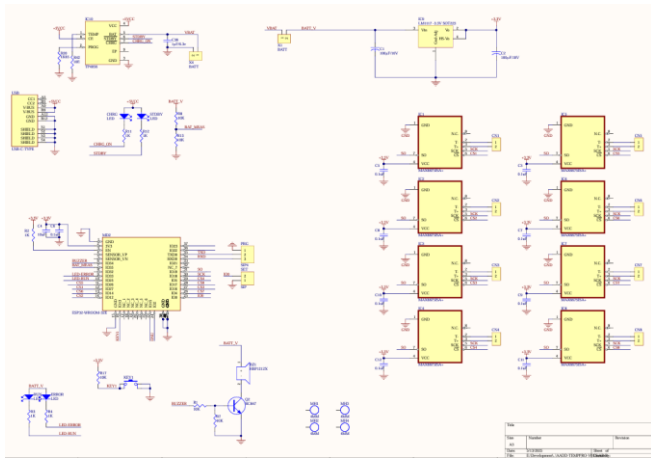


Fig. 4. Circuit Diagram

The printed circuit board (PCB) layout was developed using Altium Designer software to optimize component placement and layout routing. Power and ground planes were incorporated to improve signal integrity and thermal dissipation.

3.4 Embedded software development

The embedded firmware was developed using Arduino IDE for ESP32. The software architecture includes initialization routines, sensor polling mechanisms, communication drivers, data formatting algorithms, and error handling procedures.

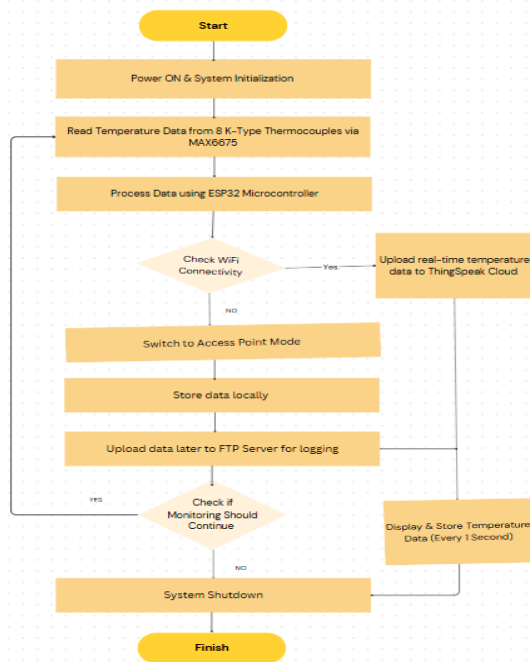


Fig. 5. System FlowChart

3.5 Data communication framework

The system supports dual mode data communication:

Real-time cloud monitoring

When Wi-Fi connectivity is available, temperature readings are transmitted to the ThingSpeak IoT platform via HTTP API requests. Each thermocouple channel is assigned to a dedicated field on the cloud panel, allowing real-time visualization of temperature trends.

Offline data logging

In scenarios where network connectivity is not available, the system stores temperature readings locally and then uploads them to a remote FTP server. Recorded data is stored in CSV format for easy import into data analysis tools such as Microsoft Excel and Power BI.

3.6 Experimental Validation Procedure

The developed temperature profiler was tested using single channel, two channel and eight channel configurations. Controlled heat sources were used to simulate the thermal conditions of the reflow oven and validate the accuracy of the sensor.



Fig. 6. Single Thermocouple Testing

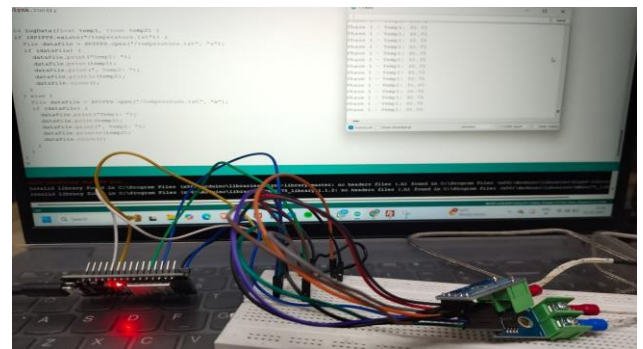


Fig. 7. Two Thermocouple Testing

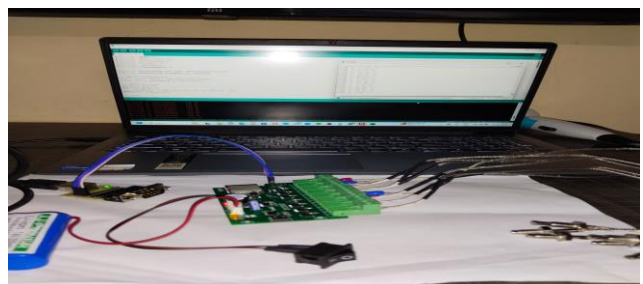


Fig. 8. Eight Thermocouple Testing

Data transmission functionality was verified through real-time cloud monitoring and offline FTP logging mechanisms.

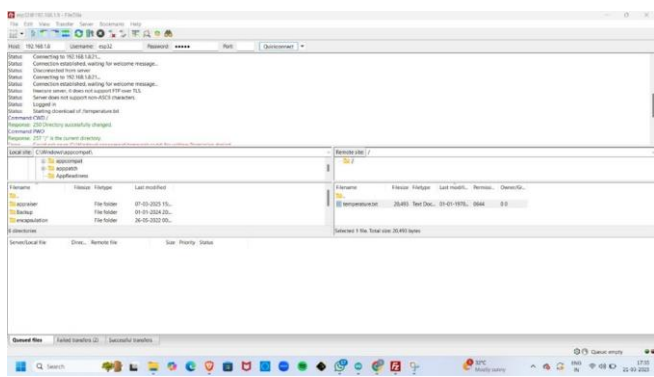


Fig. 9. FTP Temperature Data Screenshot

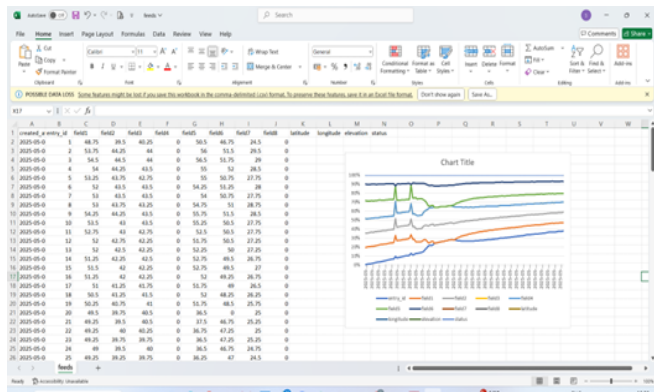


Fig. 10. Excel Analysis Graph

3.7 Methodology Outcome

The systematic design and implementation approach enabled the development of a reliable multi-channel temperature profiling system with real-time monitoring capability, offline data storage, and scalable architecture suitable for industrial and research applications. The methodology ensured proper integration of sensing hardware, communication framework, and analytical tools to achieve accurate thermal profiling performance.

IV. RESULTS AND DISCUSSION

The developed temperature profiling system was experimentally validated using single-channel, dual-channel, and eight-channel thermocouple configurations to evaluate detection accuracy, data transmission reliability, and system scalability. The results demonstrated stable temperature acquisition across all sensing channels with consistent wireless communication performance.

Real-time monitoring through the Think Speak IoT platform allowed visualization of temperature variations in different thermal zones of the reflow oven. The generated temperature curves clearly represented the acceleration, absorption, peak reflux, and cooling stages, confirming the system's ability to capture dynamic thermal behavior. Additionally, offline data logging via FTP ensured uninterrupted data collection during network unavailability.

Temperature data sets stored in CSV format were further analyzed using Excel dashboards and Microsoft Power BI to generate thermal profile graphs and comparative zone

analysis. The system exhibited a detection resolution of approximately 0.25 °C with an overall measurement accuracy of ±2 °C, which is sufficient for practical reflow soldering applications. Multi-zone monitoring helped identify temperature gradients and allowed for better process control.

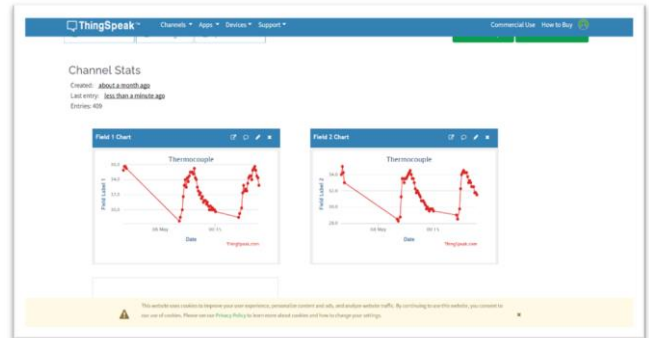


Fig. 11. ThingSpeak Field Graph

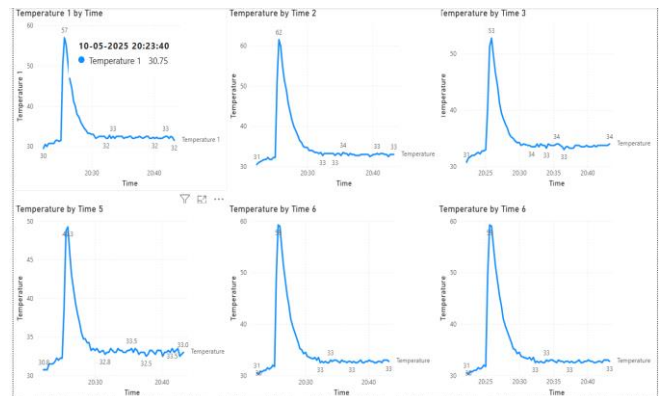


Fig. 12. FTP Power BI Visualization

Overall, the experimental evaluation confirmed that the proposed system provides reliable temperature profiling with real-time monitoring, offline logging capability, and portable deployment suitable for industrial and educational environments.

V. CONCLUSION

This research presented the design and development of an IoT-based multi-channel temperature profiler for reflow oven. The proposed system has successfully enabled real-time monitoring of temperature distribution in multiple thermal zones using ESP32 and K-type thermocouple. The integration of cloud-based visualization and offline FTP logging improves data accessibility and ensures reliable operation under various network conditions.

The developed profiler provides a cost-effective and scalable alternative to traditional industrial temperature profiling systems while maintaining sufficient accuracy for practical applications. The system enhances process visibility, supports optimization of reflow parameters, and contributes to improving solder joint reliability in SMT manufacturing.

Future work may focus on incorporating predictive analytics, mobile application interfaces, automated alert mechanisms, and closed-loop thermal control strategies to further improve system intelligence and industrial utility.

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IoT-Enabled Smart Wheelchair with Voice Control and Health Monitoring for Assistive Mobility

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Abstract: Assistance in mobility and health monitoring is vital for those with severe physical disabilities and elderly persons who are not able to operate normal wheelchairs on their own. In recent times, various smart wheelchairs have been proposed using various technologies such as voice control, obstacle sensing, and remote monitoring to provide assistance to such persons. Most of these wheelchairs are focused on mobility and lack health monitoring and emergency assistance. This paper proposes a smart audio-controlled wheelchair with health monitoring and an emergency alert system. In this proposed work, a smart audio-controlled wheelchair is implemented using a Raspberry Pi Pico 2W microcontroller, HC-SR04, MAX30102, OLED Screen, Neo-6M GPS module, wifi bluetooth module. The proposed wheelchair is controlled using voice commands such as forward, backward, left, right, and stop using a Bluetooth interface. The proposed work provides a cost-effective and efficient solution to provide mobility assistance and health monitoring and emergency assistance.

Keywords:

Smart Wheelchair, Health Monitoring, Assistive Technology, Emergency Alert System.

I INTRODUCTION

People who must use manual wheelchairs or joystick-controlled wheelchairs face major difficulties because their physical disabilities restrict their arm movements. People who face mobility restrictions experience a major loss of their ability to live independently and their overall well-being [1] [2]. The development of audio-controlled systems provides a hands-free solution that enables users to navigate through basic voice commands like "Forward," "Backward," and "Stop" which require minimal physical exertion [1] [4].

A. Problem Statement and Research Gap

Voice-controlled wheelchairs exist as accessible technology yet most current models function exclusively as

independent devices instead of delivering full assistance capabilities. The systems experience two main problems because they display operational delays through high latency while missing essential safety features [6]. The research community lacks unified systems that enable simultaneous mobility tracking and real-time health monitoring without any system interference between the two functions [12].

B. Objective and Scope of Research

The research aims to create a smart wheelchair which operates with low latency through its implementation of Raspberry Pi Pico technology. The project requires two processing cores which will handle voice recognition tasks through one core while the second core operates a "Zero-UI" safety system. This safety system uses MPU-6050 technology to detect falls and ultrasonic sensors to track obstacles, which enables immediate motor control during dangerous situations [3], [7].

C. Significance and Motivation

The motivation behind this work is to bridge the gap between assistive mobility and proactive healthcare. With its built-in MAX30102 sensor and SpO2 monitoring system, the wheelchair can connect users and caregivers alike [13]. The wheelchair system uses SpO2 monitoring and IoT-enabled MAX30102 sensor technology to create a vital link between users and their caregivers. The system provides critical support to users who have advanced neuromuscular disorders because they can experience hidden respiratory distress and fall incidents when they are by themselves [15].

D. Overview of Structure

The paper follows this structure: Section II discusses the Hardware Implementation and circuit design. The Methodology and software logic of the study appear in Section III. The Results and Discussion section presents

findings from prototype testing while Section V provides the Conclusion and future scope of the work.

II. LITERATURE REVIEW

Research has been done on various methodologies to enhance the functional capabilities, safety, and intelligence of smart wheelchairs and assistive mobility aids. For voice-controlled smart wheelchairs, the system usually includes speech recognition modules like the HM2007 or any trained voice modules, in which specific voice commands such as forward, backward, left, right, and stop are processed and controlled by microcontrollers like the Arduino Uno, which then control the DC motor movement [P1], [P2].

Some researchers have also improved the system by integrating the Bluetooth communication module and H-Bridge driver to enhance the precision of the commands and motor control [P3]. Some smart wheelchairs use sensor automation, which includes ultrasonic sensors detecting obstacles and microcontrollers processing the environment, such as humidity and GPS, to enable the safe movement of the wheelchair and the integration of safety features [P4].

Advanced speech recognition has also been implemented with the use of Digital Signal Processors (DSP) to obtain Mel-Frequency Cepstral Coefficients (MFCC) and Support Vector Machines (SVM) to control robot movement in real time [P5].

Moreover, intelligent wheelchairs with fall risk assessment capabilities using pressure sensors and machine learning techniques for analyzing sit-to-stand transitions and wirelessly transferring the data have been proposed [P6]. Also, fall detection techniques using inertial measurement unit-based fall detection models with feature extraction and anomaly detection techniques like Isolation Forest for abnormal movement of wheelchairs have been proposed [P7].

Alternative control methods for wheelchairs include head movement detection using inertial sensors, gaze-tracking techniques using facial landmark analysis, and gesture recognition techniques like Zero-UI that combine voice, motion, and vision for assistive robotics [P8], [P9], [P10].

In addition, IoT-based healthcare systems have been proposed with wearable sensor and edge computing techniques like CNN for fall detection with reduced end-to-end latency [P11].

In addition to experiments, reviews of existing literature have also been conducted using systematic and scoping review methodologies like JBI and PRISMA-ScR guidelines for analyzing socio-emotional experiences and technological trends associated with people using wheelchairs [P12]. These different methodologies underscore the accelerated progress being made regarding intelligent wheelchair technologies that incorporate voice recognition, sensor networks, machine learning, and IoT for

the enhancement of mobility and healthcare support for physically disabled individuals.

III. SYSTEM ARCHITECTURE

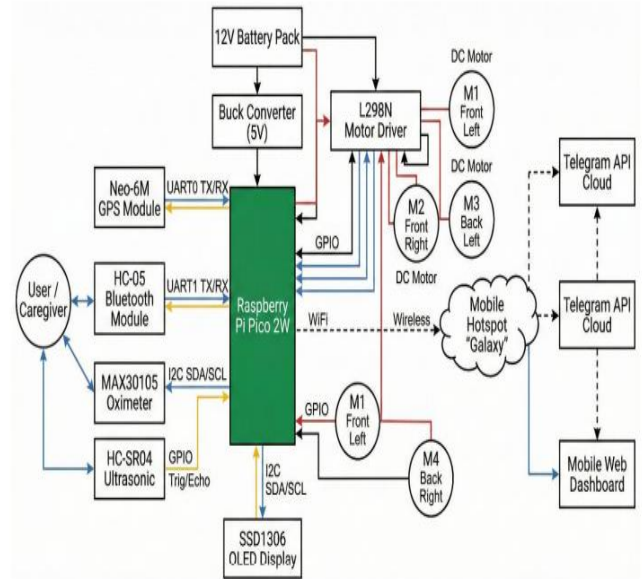


Figure 1: Block Diagram

The proposed audio-controlled smart wheelchair system offers health monitoring and emergency alert functionalities. The system block diagram displays the complete system architecture. The system combines all four functions which include mobility control and health monitoring and obstacle detection and cloud communications into a single platform. The main system component consists of a Raspberry Pi Pico 2W microcontroller. The microcontroller controls system component communication while it processes sensor information and operates the wheelchair system. The research aims to develop an automatic system which enables disabled individuals to move safely by combining embedded controllers with sensors and wireless technology in smart wheelchair systems [P1],[P3]. The documents [P2],[P12] report other designs which have implemented microcontroller systems to assist with mobility and monitoring tasks.

The hardware connections block diagram appears in Figure 1. The system establishes communication with different modules using three protocols which include UART and I2C and GPIO. The Bluetooth HC-05 module establishes a wireless link between the wheelchair and mobile devices. The current functionality enables users to issue voice commands through their smartphones. The controller interprets these commands and translates them into movement instructions for the wheelchair motors, as it goes through the L298N motor driver module. Voice control systems provide an accessible interface to assistive mobility users who cannot control traditional joystick-based

wheelchairs [P1]. The Bluetooth system enables wireless system operation while enhancing operational capabilities in wireless control systems [P11] [P12].

The MAX30105 pulse oximeter sensor functions as a health monitoring component which measures blood oxygen saturation (SpO₂) and heart rate through its sensor capabilities. The system delivers instant health information to users while establishing I2C communication with the controller. The system displays measurements on the SSD1306 OLED display while simultaneously sending them to remote monitoring systems. Health monitoring sensors in mobility devices enhance user safety through their ability to track physiological conditions in real-time [P6]. Cloud-based health monitoring systems enable remote patient observation while delivering immediate medical assistance [P13][P14].

The system uses an HC-SR04 ultrasonic sensor to detect obstacles which ensures that navigation occurs in a safe manner. The sensor operates by emitting ultrasonic waves which it uses to measure the distance between the wheelchair and any surrounding objects. The controller system will automatically stop all motor functions when it detects an object within the safety range which has been defined previously. Obstacle detection systems which use ultrasonic sensors are common in smart wheelchair systems because they enhance navigation safety and decrease the risk of accidents during operation [P3][P9][P10].

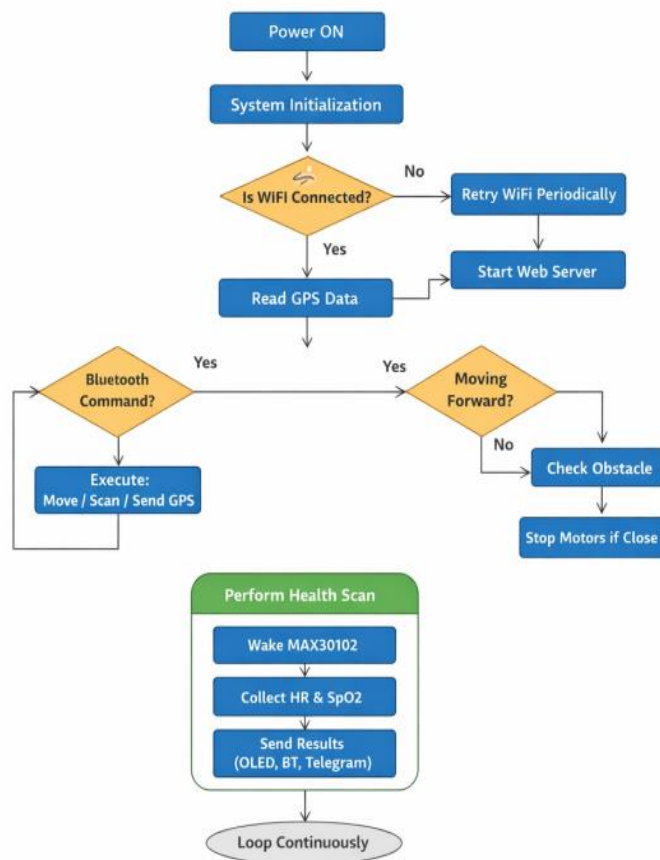


Figure 2: Workflow

The system uses a Neo-6M GPS module for tracking locations in real time. The GPS module uses a serial interface to send wheelchair location data to the controller, which updates its geographic position. Caregivers can use this location information during emergency situations. The system's workflow is shown in Figure 2. The controller initializes all hardware modules while it receives Bluetooth commands and detects obstacles and reads health parameters and transmits location and health data to the Telegram cloud platform and mobile web dashboard for remote monitoring and emergency alerts. Healthcare technologies are increasingly utilizing cloud-based monitoring and alert systems to enable real-time communication between users and caregivers [P13], [P14].

The integrated design of the wheelchair enables it to perform all functions required for mobility control and health monitoring and obstacle detection and remote communication. The system delivers a practical solution which people with mobility impairments can use in their daily activities [P1] [P3] [P6] [P12].

IV. HARDWARE IMPLEMENTATION

This wheeling wonder of technology has its heart in Raspberry Pi Pico. We chose this controller because its dual-core design allows it to handle multiple tasks at once without any lag. Essentially, the wheelchair can listen for voice commands on one core while the second core constantly monitors health and safety in the background. This dual-tasking approach makes the system much more responsive and reliable than older designs [2], [4].

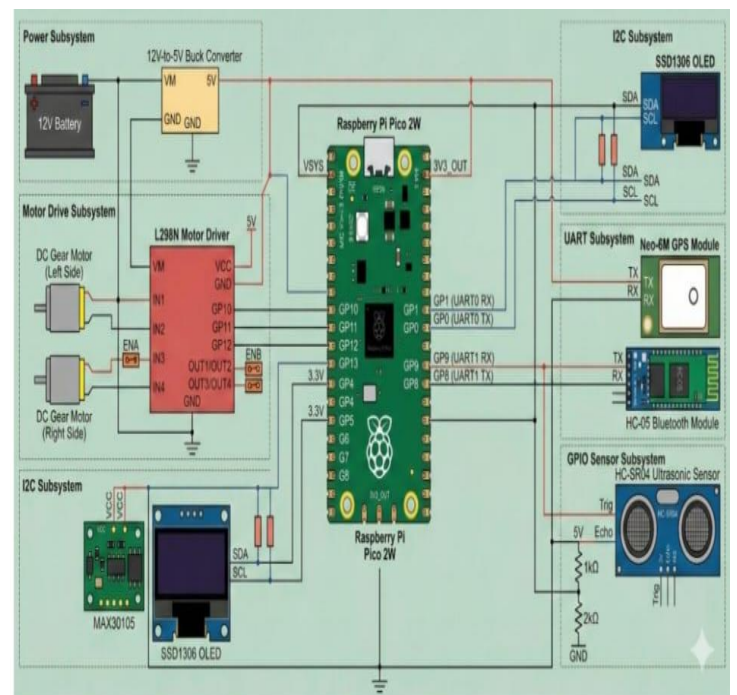


Figure 3 : Circuit Diagram

The Voice Recognition Module we installed enables

wheelchair operation through its five basic commands which include forward and backward and left and right and stop commands. The Pico system detects command execution which causes it to activate the L298N Motor Driver that functions as a power transmission system to the 12V geared DC motors. The system delivers essential torque to achieve independent movement capability while maintaining a completely hands-free user experience [1] [6] [12]. For safety, we created a "shield" using different sensors. We placed HC-SR04 ultrasonic sensors on the chair to act as eyes; if they detect an obstacle within 30cm, they trigger an automatic stop to prevent a collision [3]. We also included an MPU-6050 sensor, which monitors the chair's tilt and balance. If the wheelchair tips or the user falls, the system identifies the anomaly immediately and can send out an alert [7]. The wheelchair also functions as a health-monitoring hub thanks to the MAX30102 sensor. This small pulse oximeter tracks heart rate and oxygen levels (SpO₂) in real-time. Because the Pico handles this on a separate core, the system can monitor these vitals constantly without slowing down the wheelchair's movement, which is critical for users who need frequent health tracking [12], [13]. To keep caregivers informed, we used an ESP8266 Wi-Fi module to connect the chair to the internet. The wheelchair system enables immediate transmission of health information and emergency signals, such as falls, to a cloud service. The "Internet of Things" (IoT) integration enables distant caregivers to monitor user health status through their mobile devices or computers [13]. The complete system receives its power from 18650 Lithium-Ion batteries which serve as its main energy source. We selected these batteries because they store substantial energy capacity and deliver consistent power output which our system requires to operate both its sensors and its high-performance motors. The wheelchair functions as an environmentally friendly solution for everyday usage because its batteries can be recharged[12].

IV. RESULT AND DISCUSSION

Age (Years)	Practical Value (Sensor Reading)	Actual Value (Pulse Oximeter)
18	72 BPM	74 BPM
22	75 BPM	76 BPM
40	70 BPM	72 BPM

Table 1

The practical values obtained from the MAX30102 sensor are close to the actual readings measured using a standard pulse oximeter. This shows that the health monitoring system provides reliable and accurate measurements for different age groups.

- **Obstacle Detection Performance:**

The ultrasonic sensor is used to detect things that're in the way when the wheelchair is moving. The system is set up to

stop when something is too close, like 20-30 centimeters away. When we tested the wheelchair it could detect things in front of it. Stop by itself so it would not crash. This makes the smart wheelchair more reliable and easier to use. The wheelchair can detect obstacles and stop which's a great feature of the smart wheelchair.

- **Power System Performance:**

The smart wheelchair is powered by a battery pack that can be recharged. It has lithium cells inside. The DC-DC converter modules make sure all the parts of the wheelchair get the right amount of power. The smart wheelchair can keep going for 1-2 hours when we test it. It depends on how much the motors are working and how long the smart wheelchair is moving. The voltage regulation modules keep the power steady so the Raspberry Pi and sensors work properly.

- **Health Monitoring:**

The MAX30102 sensor is used to check the users health like their heart rate and oxygen level. We compared the sensor readings with a device to see how accurate the sensor is. When we tested the wheelchair the health information was shown on a screen on the smart wheelchair. It was updated all the time. The health monitoring system of the wheelchair gives real-time information about the user's health.

The smart wheelchair is really good at helping people get around and keeping an eye on their health. It is easy to use the wheelchair because you can tell it what to do with your voice or you can use Bluetooth to control the smart wheelchair. This means people do not have to use their hands to move the wheelchair, which is very helpful for users of the smart wheelchair. The smart wheelchair is very helpful for people with disabilities. The ultrasonic sensor makes the smart wheelchair safer by detecting things in the way and stopping the wheelchair when needed. The health monitoring part of the wheelchair gives real-time information about the user's health, which is useful for the people taking care of them. The smart wheelchair is a device for people with physical disabilities. The smart wheelchair has some limitations, like the voice commands might not work well with background noise and it is a version. To make the wheelchair work in real life we need to improve the design and how the sensors of the smart wheelchair work.

Overall the system shows that it is possible to make a device for people with disabilities by combining voice control, sensor technology and embedded systems. The smart wheelchair is an example of this.

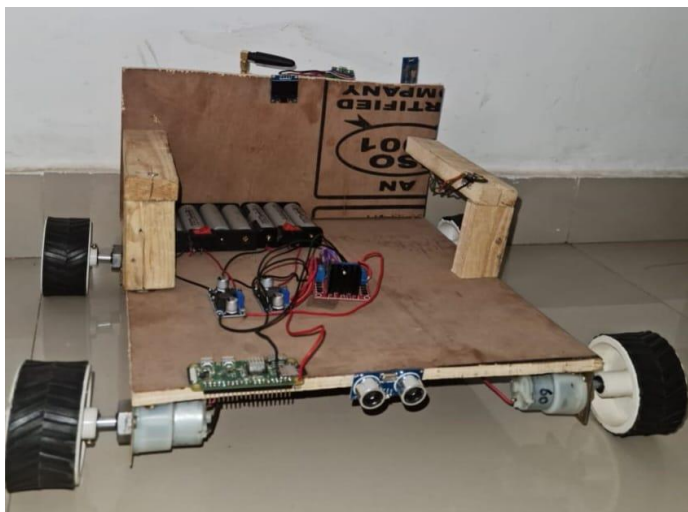


Figure 4 : Result

V. FUTURE SCOPE

The wheelchair system works well. There are things that we can do to make the wheelchair system better in the future. We can make the wheelchair system perform better, be safer and be easier to use. The wheelchair system is the thing that we are talking about.

1. **Improved Voice Recognition System:** The wheelchair system can understand some voice commands to move the wheelchair system. We can make the voice recognition system better so the voice recognition system can understand commands and work well in environments. This will make the wheelchair system easier to use. The wheelchair system will be able to understand what we want it to do.

2. **Enhanced Obstacle Detection:** The current wheelchair system uses one sensor to detect things in front of the wheelchair system. We can add sensors to the sides. Back of the wheelchair system so the wheelchair system can detect things all around it. This will make the wheelchair system safer to move. The wheelchair system will be able to avoid things that're in its way.

3. **Improved Mechanical Design:** We made a version of the wheelchair system to show how the wheelchair system works. We can make a full-size wheelchair system that's stronger and more stable. This will make the wheelchair system work better in life. The wheelchair system will be able to handle lots of use.

4. **Extended Battery Backup:** The wheelchair system uses a battery that can be recharged. We can use batteries and make the wheelchair system use power more efficiently. This will make the wheelchair system usable for a time. The wheelchair system will not run out of power quickly. The wheelchair system will keep going for a time.

5. **Advanced Health Monitoring Features:** The wheelchair system can check heart rate and oxygen levels using a sensor. We can add sensors to check health things like body temperature or blood pressure. This will help us keep an eye

on the patient's health. The wheelchair system will be able to monitor the patient's health. The wheelchair system will help us take care of the patient.

6. **Emergency Alert System:** We can add a feature that will automatically send a message to caregivers if the wheelchair system finds any health problems or unsafe conditions. This will help keep the patient safe. The wheelchair system will be able to alert caregivers in case of an emergency. The wheelchair system is designed to help patients. It will do its best to keep them safe. The wheelchair system is an important tool for patients.

VI. CONCLUSION

This paper presents a smart wheelchair which people with mobility disabilities can control through audio commands while it includes health tracking and emergency alert functionalities. The Raspberry Pi Pico 2W microcontroller serves as the main system controller which handles wheelchair operations and sensor information and system communications. The L298N motor driver operates the DC motors while the wheelchair movement follows voice commands which use Bluetooth technology. The system uses an HC-SR04 ultrasonic sensor to identify obstacles which enables secure navigation. The system uses a MAX30105 pulse oximeter sensor to track vital signs which include heart rate and blood oxygen saturation (SpO₂) and displays the data on the SSD1306 OLED display while sending it to a mobile web dashboard. The Neo-6M GPS module enables real-time location tracking while the system uses the Telegram API cloud platform to send emergency notifications which contain location data and health status details to caregivers. The proposed system delivers wheelchair users an affordable solution which improves their ability to move and stay safe while they receive health monitoring services from a distance. The future development of the system will bring better navigation abilities through artificial intelligence health assessment and advanced voice recognition.

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DigiCal: Design and Implementation of a Smart Business Calculator for Offline Financial Inclusion of MSMEs

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Abstract—While modern smartphone POS setups excel at tracking sales and taxes, they remain too expensive and internet dependent for rural MSMEs. Basic calculators solve the cost problem but completely lack transaction memory. To bridge this gap, we built DigiCal: a Smart Business Calculator that packs the logging power of POS system into a robust, everyday calculator. Powered by a Raspberry Pi, it pairs a 5×7 matrix keypad with a 3.5-inch TFT screen and secure local storage. The device logs transactions, automates GST calculations, and runs lightweight profit analytics entirely offline. Thanks to its hybrid offline first design, it functions flawlessly without a network but seamlessly supports cloud backups whenever Wi-Fi is available. By detailing its hardware and software architecture, this paper proves DigiCal is a highly practical, budget friendly solution for digitizing small retail markets.

Index Terms—Embedded Systems, Raspberry Pi Zero 2W, MSME, Smart Calculator, GST Automation, Digital Financial Inclusion, Offline POS.

I. INTRODUCTION

The Digitization of MSME financial tools means balancing affordability with functionality. Yet, a severe digital divide persists in developing markets, where retailers still rely on basic calculators and paper ledgers. Widespread mobile accounting apps often alienate vendors lacking digital literacy [1]. Hardware costs, steep learning curves, and internet dependencies simply make software only solutions impractical. Instead, these markets need zero configuration embedded devices that hide complex accounting behind familiar physical interfaces [2]. Furthermore, while mobile apps work well for personal budgeting [3], their heavy battery drain and inability to handle rapid, continuous data entry make them completely unsuitable for busy retail shops.

The latest push in IoT engineering proves that low-power microcontrollers can completely change how small businesses run. Manual tax math just doesn't cut it anymore under

strict new GST rules; vendors need automated computational models [4] that handle complex math while simultaneously logging the data for compliance [5]. In India specifically, UPI has made the actual exchange of money incredibly smooth [6], but keeping track of those payments is still a massive headache. While government policies aggressively push for rural MSME digitization [7], you simply cannot force a cloud dependent system into a town with unreliable internet. Instead, the realistic solution relies on dedicated hardware loggers [8] paired with lightweight databases like SQLite [9] to guarantee that financial ledgers survive network drops.

Standard calculators lack modern accounting capabilities, while full POS systems remain too expensive for MSMEs. To solve this, we built DigiCal: a Smart Business Calculator powered by a Raspberry Pi Zero 2W. It automates GST calculations and securely logs data offline via a matrix keypad, effectively packing robust database management into a rugged, budget friendly desktop calculator.

II. LITERATURE SURVEY

Early designs relied on Arduino to improve basic input and display mechanics [10], which paved the way for intuitive billing systems [11]. In heavily constrained settings, PIC microcontrollers minimized overhead to allow for offline transaction logging [12]. However, these basic chips simply lack the processing power needed to handle the complex, concurrent data-logging demanded by modern retail environments.

As IoT expanded into retail finance, connected accounting assistants [13] and simplified embedded dashboards proved highly effective at easing daily bookkeeping for small vendors [14]. Researchers have even tested physical calculators as entrepreneurial microlearning tools [15]. Still, current literature ignores localized databases, leaving a clear gap for fully offline systems.

To overcome microcontroller processing bottlenecks, recent architectures leverage the Raspberry Pi as a strong backbone for embedded devices. The Pi facilitates edge computing where real-time analytics and dependable local storage are strictly required [16], [17]. Benchmarks of lightweight models, like the Raspberry Pi Zero 2W, validate their energy efficiency and stability for IoT gateway services [18]. Yet, deploying these computers in standalone retail applications introduces new challenges; current research frequently fails to address the transition from general purpose IoT gateways to specialized financial logging tools.

Finally, raw processing power must be paired with ergonomic hardware interfaces [19] and secure data logging architectures [20]. Economic analyses contextualise these technical developments within India's MSME sector, showing that digital adoption directly correlates with long term business sustainability [21]. Nevertheless, developing Pi-based prototypes involves inherent trade offs. Balancing high level digital functionality, OS overhead, and peripheral interfacing [22] against the severe resource constraints of rural retail remains a complex, unresolved challenge [23] underscoring the critical need for a hybrid architecture like DigiCal.

III. PROPOSED METHODOLOGY

We developed a standalone embedded system to support offline financial operations for MSMEs, reducing dependence on cloud based POS systems. The device integrates real time GST calculation, transaction management, and secure local storage within a portable calculator like interface. DigiCal follows a simple operational loop: it accepts user input, performs required computations, stores transaction data locally, and generates summary reports. The system workflow is illustrated in Fig. 1.

A. Input Processing and Mode Selection

DigiCal boots directly into its Python based interface to reduce startup time. The system is fully keypad driven, allowing users to operate in several modes: Arithmetic, GST, Sale, Expense, Due, and Summary. Arithmetic supports basic calculations, while GST mode applies fixed tax slabs (5%, 12%, 18%, 28%). Sale and Expense modes record timestamped transactions, Due mode saves record for customer Dues and the Summary mode generates daily reports. This offline, touchscreen-free design improves reliability and makes the device suitable for low resource retail environments.

B. GST Computation and Logging Engine

DigiCal relies on a straightforward background engine to handle all tax math and save transactions. Selecting a specific GST slab depending on the item bought or sold triggers the system to calculate the applicable tax using the following formula:

$$\text{GST}_{\text{Amt}} = \frac{\text{Price} \times \text{Rate}}{100}, \quad \text{Total} = \text{Price} + \text{GST}_{\text{Amt}} \quad (1)$$

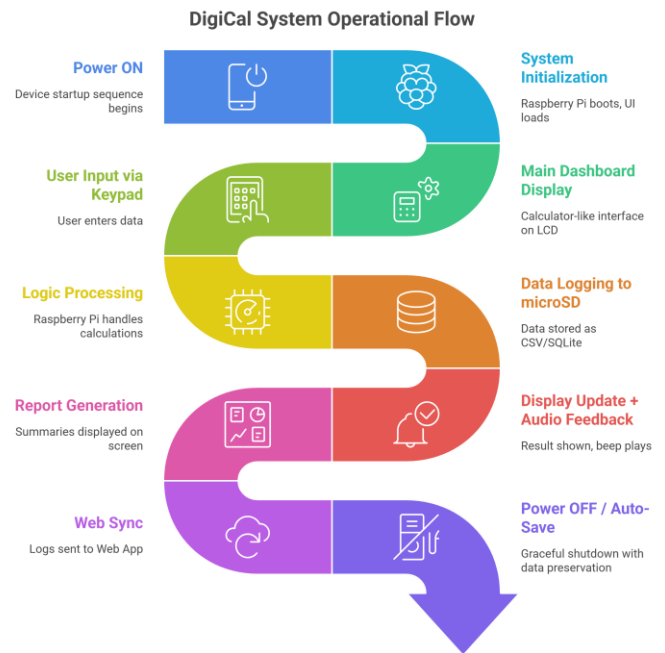


Fig. 1. system workflow for the DigiCal Smart Business Calculator.

C. Report Generation and Web Sync

DigiCal includes a built in reporting engine that allows users to view business summaries directly on the device. It processes stored transaction data to display total sales, expenses, net balance, and transaction count. Reports can be generated instantly and reset daily, while extended summaries (weekly or monthly) can be accessed through specific key inputs.

D. Web Application Integration

While the app supports entirely offline operations, there is an optional integration with a lightweight web application that allows for cloud-based analytics and visualization. Users can sync their transactions to the web application over Wi-Fi and utilize dashboards for a bird's-eye view of their sales, expenses, and profits. The web application is responsive, protected by a secure login, and supports filtering, graphical insights, and report downloads. This allows MSMEs to scale digitally using a hybrid architecture without changing anything about their current day to day experience.

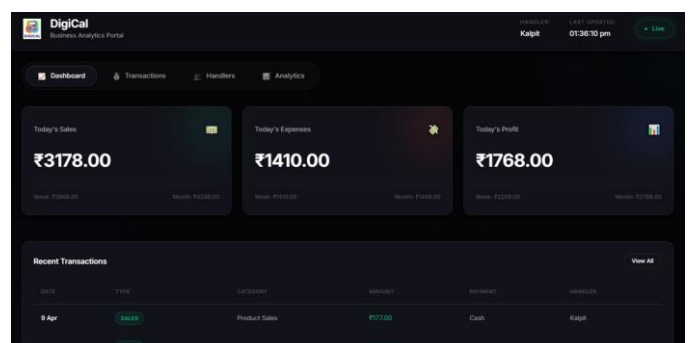


Fig. 2. Web Application

IV. SYSTEM ARCHITECTURE

DigiCal’s modular architecture makes troubleshooting simple. The User Interface relies on a 5x7 keypad, TFT screen, and speaker. Below that, the Processing Layer uses a Raspberry Pi Zero 2W to run the Python billing logic. The Storage Layer keeps financial records safe offline by housing the SQLite database and OS on a MicroSD card. To ensure portability, the Power Management Layer steps up a 3.7V Li-ion battery to 5V. Finally, the Peripheral Layer handles extras like a UPI display.

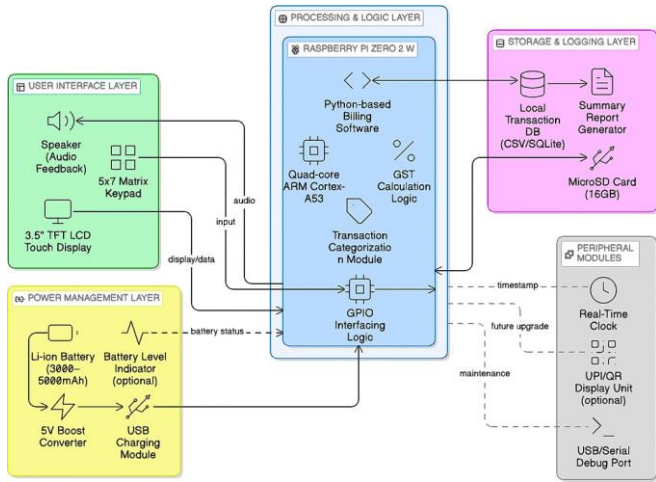


Fig. 3. Layered architecture diagram of DigiCal.

A. Circuit Diagram

As shown in Figure 4, the Raspberry Pi Zero 2W controls the entire compact circuit. A 5x7 matrix keypad wires directly into the GPIO pins for keystroke scanning, bypassing the need for a separate microcontroller. The TFT display uses the SPI protocol for rapid, pin efficient updates, alongside a standard speaker for audio cues. To guarantee portability and survive power cuts, a 3.7V Li-ion battery runs through a 5V boost converter to safely power the Pi.

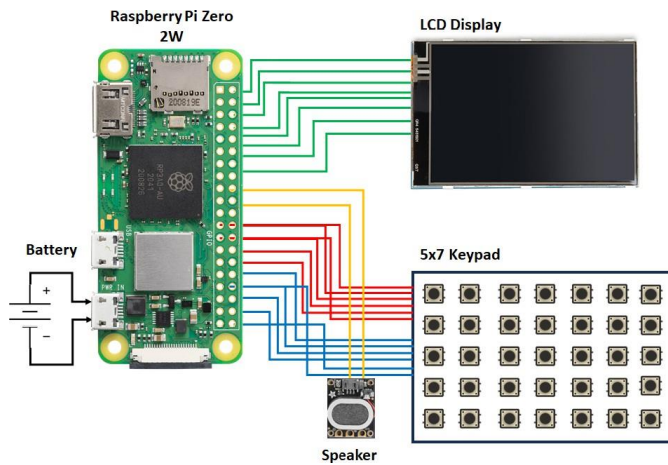


Fig. 4. Circuit schematic of DigiCal .

B. Component Specifications and Selection

1) *Processing and Display Modules:* At the heart of DigiCal sits a Raspberry Pi Zero 2W, equipped with a 1GHz quad-core Arm Cortex-A53 CPU and 512MB of RAM. We chose this board over basic microcontrollers like the Arduino or ESP32 because it easily handles a full Linux OS, native Python scripts, and local SQLite databases. Beyond packing built-in Wi-Fi, Bluetooth, and 40 GPIO pins for hardware expansion, the Pi can juggle multiple background tasks simultaneously something single threaded chips simply cannot do.

The system uses a 3.5-inch TFT LCD (480x320) connected via SPI for fast and reliable data transfer. This full color display enables smooth UI updates and supports formatted text, dynamic menus, and tabular summaries, providing a clear improvement over traditional 7-segment displays..

2) *Input Interface (5 x 7 Matrix Keypad):* To replicate the familiar experience of a physical calculator, DigiCal employs a custom 5 x 7 matrix keypad. This layout supports 35 distinct inputs while requiring only 12 GPIO pins, making it both space and pin efficient. It includes standard numeric keys, arithmetic operators, and specialized business keys such as “SALE,” “EXPENSE,” “DUE,” and “GST,” enabling quick access to core financial functions without complex navigation.

A software based debounce mechanism with a 5ms delay is used to eliminate false keypresses caused by mechanical bounce. This ensures input accuracy, which is critical during transaction entry in fast paced environments.



Fig. 5. Keypad Layout.

3) *Power Management and Audio Systems:* To guarantee true portability for rural vendors dealing with unreliable grid access, DigiCal runs on a 4000mAh, 3.7V Li-ion battery. A dedicated boost converter steps this up to the stable 5V required by the Pi, while a built-in USB module allows for easy recharging via standard phone chargers. Alongside the visual display, we integrated a compact 8-ohm, 0.5W speaker

to handle auditory feedback. Emitting clear 2kHz cues, it provides crisp beeps for keystroke confirmations and error alerts, ensuring the device remains highly usable even in loud, busy retail environments.

V. SOFTWARE IMPLEMENTATION

The DigiCal system is implemented as a lightweight embedded application using Python on Raspberry Pi OS. Instead of relying on multiple independent processes, the system follows a single continuous control loop that manages input, processing, storage, and output in real time. This approach reduces overhead and ensures predictable performance during frequent transaction operations.

A. Execution Flow

When the device powers on, the application starts automatically and initializes all required interfaces, including GPIO pins, display drivers, and the local database. The system then enters a continuous loop where it performs the following sequence:

- 1) Scan keypad input using row-column mapping
- 2) Identify the selected mode (Arithmetic, GST, Sale, Expense, Due, Payment, Summary)
- 3) Process the input based on the selected mode
- 4) Compute required values (e.g., GST or totals)
- 5) Store transaction data in the local database
- 6) Update display output and generate audio feedback
- 7) Check for optional synchronization when network is available

This loop repeats continuously, allowing the system to respond instantly to user inputs without noticeable delay. Figure 6 shows key software interface screens of DigiCal transaction workflow.

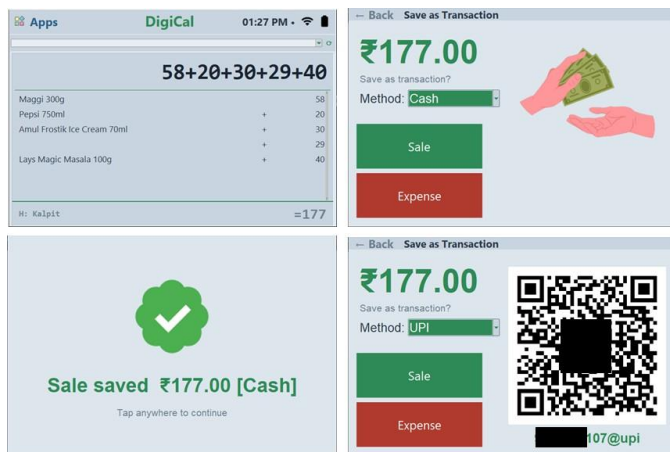


Fig. 6. DigiCal transaction interface.

B. Core Functional Modules

1) *Input and Interface:* The keypad is scanned using GPIO row-column detection with software debouncing to ensure reliable input. Each valid keypress is mapped to the selected function, while the TFT display provides real time updates. Audio feedback is used for confirmations and alerts.

2) *Computation and Storage:* Arithmetic, GST, and transaction calculations are processed instantly using predefined tax slabs. Confirmed transactions are stored in a local SQLite database with timestamps to ensure reliable record keeping.

VI. RESULTS AND PERFORMANCE ANALYSIS

The DigiCal system was evaluated under practical usage conditions to analyze computational performance, reliability, and system functionality. Figure 7 presents key interface outputs of DigiCal, including customer due management, transaction history, and sales, expense analytics. These outputs demonstrate the system's ability to handle transaction logging, customer record management, and business performance analysis in real time.

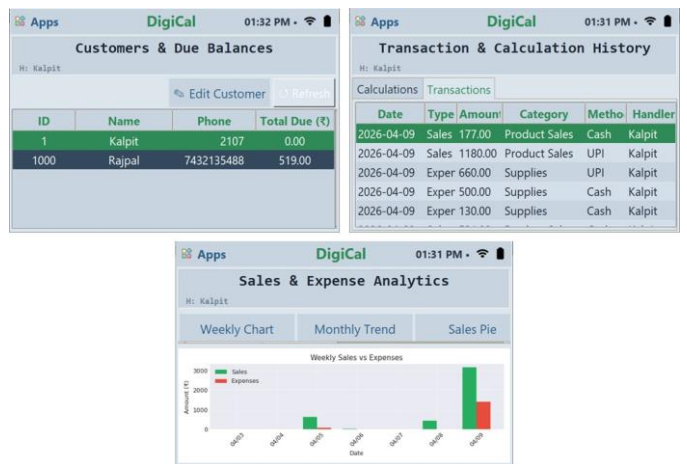


Fig. 7. DigiCal interface

A. System Performance

The device achieved a boot time of approximately 15–20 seconds, after which the application was directly accessible. Keypad input response was observed to be near instantaneous (less than 50 ms), enabling smooth transaction entry. Arithmetic and GST calculations were performed in real time with negligible delay.

The system was also able to handle background tasks such as data logging and analytics without affecting user interaction, demonstrating effective multitasking capability.

B. Accuracy and Data Reliability

To verify computational accuracy, multiple transactions were tested across different GST slabs (5%, 12%, 18%, and 28%). The system consistently produced correct results, achieving 100% accuracy in GST and total value calculations.

All transactions were successfully stored in the local SQLite database with timestamps. No data loss was observed during testing, indicating reliable storage performance.

C. Analytics and Synchronization Performance

The integrated analytics module generated daily summaries including total sales, expenses, and net profit. Basic trend

estimation using recent transaction data was successfully demonstrated without impacting system responsiveness.

The hybrid offline-first synchronization mechanism was tested under intermittent network conditions. All data was stored locally during offline operation and successfully uploaded when connectivity was restored, ensuring continuous operation without dependency on internet availability.

D. Power Consumption

The system consumed between 2.3 W and 3.5 W during operation. With a 4000 mAh battery, the device provided an average runtime of 2–3 hours under active usage, making it suitable for typical daily business activities.

E. Comparative Analysis

A qualitative comparison was performed between DigiCal, traditional POS systems, and mobile based accounting applications to evaluate practicality and usability in MSME environments. This demonstrates DigiCal's advantage over traditional POS systems in terms of cost, reliability, and offline usability.

TABLE I
COMPARATIVE ANALYSIS OF DIGICAL WITH EXISTING SOLUTIONS

Parameter	DigiCal	POS System	Mobile App
Cost	Low	High	Medium
Internet Requirement	Not Required	Required	Required
Portability	High	Low	High
Ease of Use	High	Medium	Low
Transaction Speed	Fast	Medium	Slow
Data Storage	Local (Offline)	Cloud-based	Cloud-based
Analytics Support	Basic (Local)	Advanced	Moderate
Reliability	High	Low	Low

VII. CONCLUSION AND FUTURE WORK

We developed DigiCal to actively bridge the digital divide for local MSMEs. By packing automated GST math, transaction logging, and daily summaries into a familiar calculator layout, it offers a tough, budget-friendly alternative to complex POS systems. The hardware relies on a Raspberry Pi Zero 2W, a 5 x 7 matrix keypad, and a TFT display, allowing non-technical vendors to securely track their finances completely offline. Ultimately, this modular design makes it a highly practical fit for everyday use in rural retail shops.

Looking beyond the current prototype, the hardware can easily expand to handle physical retail demands like printing paper receipts via a Bluetooth thermal printer. We could also hook up cheap USB barcode scanners for strict inventory tracking. On the software side, the processing ceiling can go much higher. Instead of basic statistical analytics, running a quantized mini LLM entirely on the device would let vendors query their SQLite database using natural language. Finally, adding a solar harvesting circuit would make the system completely self sustaining off the grid.

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IoT-Enabled Intelligent Motor Protection and Monitoring System for Agricultural Irrigation Pumps

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Abstract—IoT based Smart Motor Protection and Monitoring System for single phase agricultural irrigation pumps using ESP32 microcontroller board and different sensing modules. The proposed system continuously monitors the voltage and current supply current as well as the hydraulic output of the pump. It consists of ESP32 microcontroller board along with ZMPT101B AC voltage sensor, ACS712 Hall effect current sensor and YF-S201 water flow sensor. It has a relay module which is controlled by the microcontroller for disconnecting the motor supply instantly in the event of any faults like under or over voltage and under or over current. The real time data is transmitted wirelessly using Wi-Fi connectivity through MQTT protocol to a Node-RED dashboard which is displayed on the mobile application of the farmers for remote access and control. The proposed system helps in the determination of the irrigation efficiency by comparing the energy consumed by the motor with the actual water flow produced which acts as an indicator of potential faults in the pump. The accuracy of the voltage and current measurements as well as the instant of relay switching was tested and it was found that the measurement of voltage has an accuracy of ± 1.5 V, measurement of current has an accuracy of ± 0.2 A and relay switching instant has an accuracy of 500 ms for all the faults tested. The proposed research work aligns with the theme of the conference "Clean and Green Village: Rural Transformation" as stated in TKD-26.

Keywords—IoT, Agricultural Motor Protection, ESP32 microcontroller, ZMPT101B Voltage Sensor, ACS712 Current Sensor, YF-S201 Flow Sensor, MQTT Protocol, Smart Irrigation, Rural Transformation, Embedded Systems.

. INTRODUCTION

There is no dedicated electrical protection other than a standard fuse for all motors in India. Adequate electrical protection for motors is far from being the ground level in India. Such elementary protection as a circuit breaker would provide a higher level of protection against unreliable rural supplies. Transient voltage spikes, voltage sags and prolonged periods of undervoltage are a common phenomenon on rural distribution networks and have harmful effects on the motor windings.

The second problem is less talked about: farmers do not have visibility of the actual pump operations. They have no way of knowing that the motor is on, or when it may trip out, or if the water is ever reaching the field. Power is often available only during late-night hours, which means site visits happen at inconvenient and sometimes unsafe times. This imposes unnecessary labour and, when faults go undetected, directly increases the risk of crop loss.

Affordable IoT hardware has now made it realistic to tackle both problems at once. At under ₹300 with integrated 802.11 Wi-Fi, the ESP32 microcontroller provides a practical foundation for a protection and monitoring platform [10]. Prior work has addressed pieces of this problem, GSM-based remote pump switching and soil-moisture-driven irrigation scheduling have both been demonstrated in the field, but no published system has brought real-time electrical protection, water flow monitoring, and remote control together into a single unit designed for rural single-phase pumps in India. That is the gap this work fills.

The system continuously monitors the supply voltage and motor current and trips the relay within 500 ms of any fault. The water application rate is continuously monitored and data is transmitted to the farmer's smartphone using MQTT protocol. This work is directly related to the TKD-26 theme of Clean and Green Village: Rural Transformation, as effective motor protection is always linked with energy saving and crop loss reduction in rural communities where pump failures cause significant damage.

This work provides four important contributions: (1) a single board for the rural single-phase induction motors that can provide undervoltage, overvoltage and IEC 60947-4-1 time delayed overloads protections; (2) water flow measurement and irrigation efficiency calculation that can be integrated along with protection relays; (3) Node-RED MQTT based remote control of the motor along with live monitoring on any smartphone connected to internet. The performance of the proposed system has been validated through a set of experiments conducted on six different operating scenarios with exact measurements of the accuracy

and response times. All the hardware components are estimated to be available for less than ₹3,000.

I. LITERATURE REVIEW

Despite a growing number of papers on IoT solutions for agriculture, they tend to only address aspects of motor protection and monitoring. The research papers reviewed here are some of the closest to the proposed contribution.

Patil et al. [1] reported on a smart soil moisture based IoT irrigation controller that claimed to reduce the water consumption by around 30% in a field trial experiment. While the water was supplied to the required satisfaction, the pump motor had no protection at all, as often the case, against the voltage fluctuations that are very common on the rural distribution networks in India. Kumar and Bhatt [2] reported on GSM based remote control of agricultural pumps using SMS. The pumps were said to be switched on and off as required in the area where internet connectivity is not available. No sensing was provided to find out the state of the motor after switching on.

The work of Mehra et al. [3] is the closest to addressing the protection problem using current and temperature monitoring with IoT connectivity for three-phase industrial motors. As we know that three-phase industrial machines behave very differently than the small single-phase induction motors used in the rural grid level motors. So their protection thresholds, inrush current characteristics and their failure modes will not match to that of small grid level induction motors. Sharma et al. [4] have made an extensive evaluation of ZMPT101B voltage sensor for the purpose of AC measurement in an embedded system and their experiment results reveal that their measurements are accurate to within $\pm 2\%$ in the range of 180–250 V. In our sensor selection work, we will largely refer to this article.

IoT based real time motor protection and automated fault alert using flow sensor Khan et al. [5] give a good survey of applications of IoT in precision agriculture. They highlighted real-time motor protection and automated fault alerting as two priority unsolved challenges for smallholder farmers in developing countries - the challenge addressed in this paper. Tambe and Khandekar in [6] verified that the readings of the YF-S201 flow sensor in an agricultural pipeline were highly accurate with errors ranging from $\pm 5\%$ in the flow range of 1–30 L/min. In [7] Bhonge and Bapat verified that nodes based on the ESP32 micro-controller maintained reliable communication through MQTT over the typical rural Wi-Fi infrastructure in Indian farms with packet delivery rates exceeding 99% for QoS Level 1.

Although we have consulted all the literature that have been developed on a basis for each of the components that will make up the remote management system for irrigation in rural areas, such as voltage monitoring, current measurement, flow measurement, among others, communications with MQTT protocol and above all the remote control of pumps, everything has been already done. Now it is to integrate all validated items in a single technological device, for the integral use in irrigation systems of a rural single-phase type, with the purpose of making it a complete and operational system of Smart Irrigation, as proposed.

II. PROPOSED SYSTEM

This product is a compact control unit that mounts in the motor starter panel of a pump. It integrates the following functions: power monitoring, motor protection, flow measurement and remote communication. The performance criteria are detailed below.

Voltage drop or surge causing the supply voltage to fall below 180V or to rise above 250V will trigger the relay to switch OFF within 500ms of the voltage crossing the threshold.

Pickup at sustained overloads of the motor current (beyond 110% of nominal value) and after a time delay of 3 seconds according to IEC 60947-4-1. To avoid unwanted tripping due to start-up inrush currents.

Measure the instantaneous volumetric flow rate and accumulate the total water volume delivered per irrigation session.

Estimate overall irrigation efficiency by computing the ratio of hydraulic energy delivered to electrical energy consumed.

Enable remote ON/OFF motor control from any internet-connected smartphone via the MQTT-based dashboard.

Transmit an immediate push notification to the operator dashboard upon any protection event.

Alarm Conditions

Before we dive into the inner workings of the protection relays and control board, one design decision is important to acknowledge. The relay is always de-energised before an alarm is sent. In other words, protection always comes first. Remote restart of the motor is disabled until it is verified that the fault condition has been removed, thereby eliminating the chance of unintentionally powering the motor back up into a problematic electrical supply. This will be discussed in further detail in Section V.

III. SYSTEM ARCHITECTURE

System divided into three main layers such as hardware layer (sensing and actuation), ESP32 layer (processing and communication) and the application layer on the farmer's smartphone.

Sensing and Actuation Layer

Every part of the motor circuit as well as the water pipe are situated in this enclosure. The ZMPT101B measures the mains voltage across the AC supply line with a scaled analog output proportional to the supply voltage. In series with the motor run lead is an ACS712 30A current sensor [8], once again without any isolation required thanks to the Hall-Effect principle. On the pump discharge pipe is an YF-S201 water flow sensor, with an output consisting of a pulse train whose frequency is directly proportional to the amount of water flowing. The single-channel opto-isolated relay module is used to switch the motor on and off under ESP32 control.

Processing and Communication Layer

The ESP32 DevKit v1 features an Xtensa LX6 dual-core 32-bit CPU with a clock rate up to 240 MHz, a sensor sampling and protection core and a Wi-Fi/MQTT communication core. The communication core with its Wi-Fi 802.11 b/g/n wireless interface is separated from the sensor

sampling and protection core, so that any communication delay caused by WiFi problems does not interfere with the protection core. External radio module is not required.

B. Application Layer

The Node-RED dashboard can be hosted on a web server located on the development machine or server in the Cloud hosting the Pi and is subscribed to the MQTT broker that hosts the data. This data is displayed as a voltage gauge, current as a graph of the last second, flow rate as a value for the last second and as a fault log with date-stamped entries.

IV. METHODOLOGY

A. Voltage Sensing and Calibration

Using the isolation on the ZMPT101B together with the built-in precision op-amp, the ESP32 is able to measure a replica of the low-voltage mains ac waveform with a maximum excursion from its mean value of less than 10% of full scale, as a direct connection can be made to the ADC input of the board without damage. Sampling is at 25 kHz and it has 500 points in a 50 Hz cycle. The voltage is then calculated with the standard discrete algorithm for True RMS calculations. The calibration involves measuring two voltage points with a Fluke 87V multimeter in order to deduce the other points required for the calibration routine by measuring the input to the ADC via a DVM. The undervolt and over-volt trigger points were fixed at 180 V and 250 V respectively. These limits are based on references found for protection circuits for agricultural motors of the type deployed on Indian rural feeders.

B. Current Sensing and Overload Detection

The limit is set at 66 mV/A and the 30 A output of the sensor is biased to a mid-rail level of 12.5 V for the calculation of the RMS current measurement of the same 500 samples as for the measurement of the RMS of the supply voltage, using the standard discrete approximation method. However, the current relay in the module is not tripped on the first occasion of a detected over current value. The firmware includes a three second timer that can only trip the relay if the measurement of I_{RMS} of the supply current during the whole duration of the timer is greater than 110% of the rated value of the current for the motor being tripped. This method of setting of the over current relay trips only after the time has elapsed when a high inrush current is established by the motor during start up and the inrush current has subsided to within the safe limits of 110% of the full load current value in the same way as a thermal overload relay as described by IEC 60947-4-1 for the protection of motors.

C. Water Flow Measurement

The volume of water for each flow measurement is given by the YF-S201 calculation of the rate of the pulses that the rotor of the magnet type flow sensor generates from the interaction between a rotor mounted permanent magnet and a hall effect switch. The count of the pulses as done in this project is done via a hardware interrupt by connecting the flow sensor switch to an ESP32 GPIO pin as a way of avoiding the loss of some counts in the measurement flow due to processor being engaged in processing the data from other pins.

where Δt is the elapsed measurement interval in minutes. Integrating Q over the motor's run time gives the total volume delivered to the field for that irrigation session.

D. Motor Efficiency Estimation

The irrigation efficiency of the flow to the field is calculated based on a density of water of 1000 kg/m³, gravitational acceleration of 9.81 m/s², the head of water specified by the farmer in the dashboard, and volume of water flow as shown in Eq. 3. Not a precision measurement, but changes with pump condition. An impeller that is worn out or a discharge pipe that is partially blocked may reduce efficiency of the pump over a period of time before they reduce the head sufficiently to cause a fault. Very useful as an early warning indicator.

where ρ is water density, g is gravitational acceleration, H is the static head, and V_{water} is the volume delivered. Static head is entered once by the farmer through the dashboard. Although not a precision measurement, this efficiency index is genuinely sensitive to pump degradation, a worn impeller or a partially blocked discharge pipe will cause a measurable efficiency drop well before the problem becomes severe enough to trigger a fault condition, making it a practical early-warning tool.

E. MQTT Communication

Every second the ESP32 serialises V_{RMS}, I_{RMS}, flow rate, active power, efficiency, and relay state into a compact JSON string and publishes it to a locally hosted Mosquitto broker on the topic farm/motor/data. So after testing with QoS 0 on the ESP32 we were experiencing packet loss when the switch of the autotransformer caused a short disruption of the Wi-Fi connection on the ESP32 board. By setting QoS to 1 the broker will then acknowledge when it has received the packet, and the ESP32 will store the unacknowledged packets in a queue, and will send them when the link comes up again. We are receiving the control messages for the farm/motor/control topic. The average round trip time for this has been about 320 ms, and we don't see this as being an issue for manually switching a pump on and off.

V. BLOCK DIAGRAM

Fig. 1, The complete block diagram of the system functional blocks with the respective sections highlighted by colour bands showing power supply to the board (dark blue), and the respective functional blocks on sensing and actuation (green), processing (blue), communication (purple), and application (red).

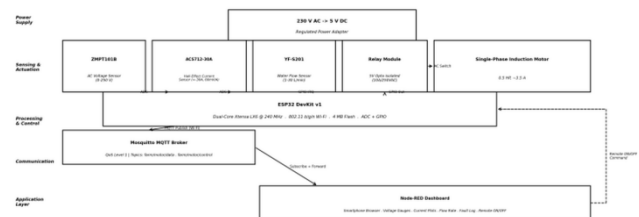


Fig. 0. System Block Diagram of the Proposed IoT-Based Motor Protection and Monitoring System

VI. SYSTEM FLOWCHART

Fig. 2, Flow-chart of the firmware running in the ESP32; showing power-on state and the loop in the steady-state. The

respective states of the YES and NO exit paths at the diamonds are shown inside the respective rectangles.

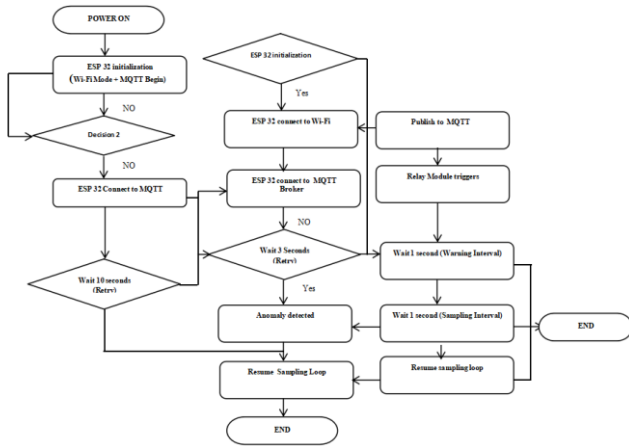


Fig. 1. Firmware Operational Flowchart of the Proposed System

VII. EXPERIMENTAL SETUP

The prototype was assembled on a standard development board in a polystyrene enclosure and tested in the department's Electronics Laboratory. Supply voltage was varied using a Variac transformer; overload conditions were simulated with a calibrated series resistor bank. The YF-S201 was bench-calibrated against a graduated cylinder with an average deviation under 0.4 L/min. All voltage and current readings were cross-checked against a Fluke 87V multimeter and a calibrated clamp-type current probe.

TABLE . HARDWARE COMPONENTS USED IN THE PROTOTYPE

S.No.	Component	Specification / Model	Purpose
1	Microcontroller	ESP32 DevKit v1 (Dual-core 240 MHz, 4 MB Flash, Wi-Fi/BT)	Central processing, ADC sampling, Wi-Fi, relay control
2	Voltage Sensor	ZMPT101B (0–250 V AC, isolation transformer + op-amp)	AC mains voltage monitoring and protection
3	Current Sensor	ACS712-30A (Hall effect, ± 30 A, 66 mV/A)	Motor current monitoring and overload detection
4	Flow Sensor	YF-S201 (1–30 L/min, 5 V pulse, 7.5 pulses/L)	Water flow rate and volume measurement
5	Relay Module	Single-channel 5 V relay, 10 A / 250 V AC	Motor ON/OFF and fault disconnection
6	Power Supply	230 V AC to 5 V / 2 A DC adapter	Power for ESP32 and sensors
7	Load (Test)	0.5 HP single-phase induction motor (≈ 3.5 A)	Simulated agricultural pump
8	IoT Platform	Node-RED + Mosquitto MQTT Broker v2.x	Visualisation, remote control, alerts
9	Communication	Wi-Fi Router (802.11n, 2.4 GHz)	ESP32-MQTT connectivity
10	Dev. IDE	Arduino IDE 2.3 with ESP32 Package	Firmware development

VIII. RESULTS AND DISCUSSION

The individual fault tests were carried out, after which the system was left to operate indefinitely for 72 hours to confirm that the Wi-Fi and MQTT protocol stack behaves suitably in continuous operations. Tests covered six scenarios: two under normal operating conditions (T1 and T2), an

undervoltage (T3), an overvoltage (T4), an overload alone (T5), and a low voltage in addition to an overload (T6).

Relay response times are well under the 500 ms target. For the single fault tests, the relay operation time during the undervoltage test (T3) was 480 ms, and during the overvoltage test (T4) was 420 ms. The combined fault test (T6) had the fastest operation time of 390 ms. Although both protection paths were triggered in T6, the firmware took the time of the first operation. The 3-second time in T5 is not a long time. It is required by IEC 60947-4-1 thermal-relay practice, to avoid tripping due to high inrush current associated with motor start-up.

Even during the most erratic swings in supply voltage, the accuracy of measurement held up remarkably well. The voltage error was always within ± 1.5 V of the Variac standard and never exceeded -1.4 V at under-voltages or $+1.2$ V at over-voltages, the relative error was never more than 0.87%. The current error was always within ± 0.2 A, or about 3.3% of the motor's nameplate current.

We see that the irrigation efficiency was estimated at 58.2% for T1 and 56.7% for T2. These results are generally in line with the theoretical value of 58.7% for the lightly loaded 0.5 HP single-phase motor. In any case, there was no communication failure requiring human intervention during the whole duration of the test with 99.8% of MQTT messages (QoS Level 1) being sent as required, and no unexpected shutdown of the system.

TABLE I. EXPERIMENTAL RESULTS, SYSTEM PERFORMANCE UNDER TEST CONDITIONS

T#	Test Condition	Set V	Meas. V	Meas. I	Flow	System Response
T1	Normal	230	228.7	2.4	12.3	Motor ON. No fault.
T2	Normal	220	218.9	2.5	11.8	Motor ON. Eff: 58.2%.
T3	Undervoltage	170	169.4	3.1	8.6	Relay OFF 480 ms.
T4	Overvoltage	270	271.2	2.2	13.1	Relay OFF 420 ms.
T5	Overload	230	229.1	5.8	10.9	Relay OFF 3 s delay.
T6	Low V+Overload	165	164.6	6.2	7.4	Relay OFF 390 ms.

IX. IMPACT ANALYSIS

The cost of a single-phase induction motor for agricultural use in rural India typically ranges from ₹8,000 to ₹25,000. When a motor burns out due to voltage fluctuations or sustained overcurrent, farmers must purchase a replacement, which represents a significant financial burden. The proposed system costs less than ₹3,000 in hardware components, meaning that preventing even one motor burnout through timely fault detection recovers the system cost 3 to 8 times over. Beyond equipment protection, the system eliminates the need for site visits during off-peak hours when power is available. Currently, farmers must travel to the field at inconvenient times—often late night—simply to verify whether the pump is running or has tripped. Remote monitoring via smartphone removes this labour requirement entirely, freeing time and resources that would otherwise go to checking on equipment.

Pump failures during critical irrigation windows directly threaten crop yield and quality. The proposed system's relay switching within 500 milliseconds prevents motors from running under damaging voltage conditions, which is the

primary cause of winding deterioration in rural distribution networks. Beyond protection, the water flow measurement capability provides farmers with exact data on how much water reached the field—information that was previously unavailable without expensive instrumentation. The efficiency index calculated from voltage, current, and flow data serves as an early warning indicator. When efficiency drops from its baseline—such as from 58% down to 40%—it signals a worn impeller, blocked intake, or partial bearing failure before these conditions lead to complete motor shutdown. This early detection allows planned maintenance rather than emergency replacement.

Motors operating under low voltage draw disproportionately high current to deliver the same mechanical power, causing unnecessary electrical losses in the rural feeder network. When pump efficiency degrades—for example, from the measured 58.2% to 40%—the system must consume 45% more electrical energy to deliver the same volume of water. By maintaining motor health and detecting efficiency loss early, this system reduces wasted electricity on rural distribution networks that are already stressed. Preventing frequent motor replacements also reduces electronic waste entering the environment. These benefits align directly with the conference theme of “Clean and Green Village: Rural Transformation,” where energy conservation and resource protection are essential for sustainable rural development. The system demonstrates how low-cost technology can deliver environmental gains without requiring farmers to make expensive infrastructure changes.

X. CONCLUSION

This paper has presented an IoT-based motor protection and monitoring system for single-phase agricultural irrigation pumps [9], built around an ESP32, ZMPT101B voltage sensor, ACS712 current sensor, YF-S201 flow sensor, relay module, Mosquitto MQTT broker, and Node-RED dashboard. The system gives farmers continuous visibility into motor health, trips the relay within 500 ms of any fault, and allows remote motor switching from any smartphone, all for under ₹3,000 in hardware.

Results from laboratory testing were consistent and encouraging. Voltage accuracy stayed within ± 1.5 V and current accuracy within ± 0.2 A across all six test scenarios. Every fault condition produced the correct relay response within the required time. Over the 72-hour endurance trial, there was not a single unrecovered communication failure, delivering a 99.8% MQTT message rate at QoS Level 1 and no unexpected system resets.

It is very important to keep in mind that the results were obtained in a very controlled laboratory setting and there are numerous challenges which will arise when the technology is deployed at a farm, managing heat and humidity in enclosures, mitigating the effects of EMI from other farm equipment and dealing with poor mobile network connectivity at rural farm locations. The next phase of the project will see the extension of the platform to three phase motors with the ability to detect phase imbalance, addition of a GSM fall back to deal with areas where Wi-Fi is not available and the deployment of a predictive maintenance indicator which will utilize trends in long term motor efficiency. The next stage will involve deployment in field trials on working farms in Marathwada and Vidarbha.

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AUTOMATED RAINWATER HARVESTING SYSTEM

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Abstract—Water scarcity is a major problem due to increasing population and irregular rainfall. A large amount of rainwater is lost as runoff because of the lack of proper management systems. This paper presents an IoT-based Automated Rainwater Harvesting System using an ESP32 microcontroller for efficient collection, monitoring, and utilization of rainwater. The system uses a rain sensor to detect rainfall and automatically starts water collection through a valve into a storage tank. An ultrasonic sensor monitors the water level to prevent overflow, and an outlet is provided to safely discharge excess water when the tank is full. A pH sensor is used to check the quality of stored water, and based on this, water is transferred to a secondary tank for drinking purposes. LED indicators are used for visual monitoring of system status. A web-based dashboard is developed to display real-time data such as rain status, water level, pH value, valve status, and history of readings. The system ensures efficient water management, reduces wastage, and supports sustainable use of rainwater resources.

Index Terms—Rainwater harvesting, IoT, ESP32, water level monitoring, pH sensor, automation, smart water management, web dashboard, sensors, sustainability

I. INTRODUCTION

Rainwater harvesting is an effective method of collecting and storing rainwater for future use [10]. It has been used since ancient times to manage water resources and reduce dependency on groundwater. Traditional systems such as rooftop collection and storage tanks help in conserving water, especially during dry seasons.

In the present scenario, water scarcity has become a serious issue due to rapid population growth, urbanization, and changing climatic conditions [1], [2]. Irregular rainfall and excessive use of groundwater have further increased the problem. Although a significant amount of rainfall occurs every year, a large portion of it is lost as runoff due to the lack of proper collection and management systems.

Conventional rainwater harvesting systems are mostly manual and do not provide proper monitoring of water level and water quality. This can lead to problems such as overflow, wastage of water, and usage of contaminated water. Therefore, there is a need for a smart and automated solution to improve efficiency and reliability [3].

The proposed system is an IoT-based Automated Rainwater Harvesting System using an ESP32 microcontroller. It uses a rain sensor to detect rainfall and automatically initiates water collection through a valve into a storage tank. An ultrasonic sensor monitors the water level to prevent overflow, while a water quality sensor evaluates

the suitability of stored water. Based on the quality, water is either transferred to a secondary tank for drinking purposes or used for non-drinking applications.

The system also includes LED indicators for visual monitoring and a web-based dashboard for real-time data display, including rain status, water level, water quality, valve status, and historical records. This ensures efficient water management, reduces wastage, and promotes sustainable use of rainwater resources.

The novelty of the proposed system lies in its intelligent decision-making capability, where water is automatically classified and distributed based on quality parameters. Unlike conventional and existing IoT-based systems, it integrates dual-tank management, real-time monitoring, and automated control to optimize water usage efficiently and improve overall system performance.

II. LITERATURE REVIEW

Several research studies have explored automation in rainwater harvesting systems using embedded technology and IoT. Smart Rainwater Harvesting System Using IoT (2025) – Authors developed an IoT-based system for efficient rainwater collection and monitoring. Smart Rainwater Harvesting Using Real Time IoT (2025) –

Developed a real-time IoT-based smart rainwater harvesting system for automated water collection, purification and monitoring.

IoT-based Agriculture Automation and Rainwater Harvesting System (2024) – Developed System to monitor and collect rainwater for agricultural and other uses.

Smart Rainwater Harvesting System (2023) – Designed an IoT-based smart rainwater harvesting system for monitoring water quality and level in real time.

IoT-based Automatic Rainwater Harvesting And Irrigation System (2022) – Designed IoT based smart rainwater harvesting system to monitor online and collect water.

From the literature, it is evident that combining IoT with traditional rainwater harvesting greatly improves monitoring, storage, and resource distribution. However, a fully integrated and intelligent system with filtration, control, and analytics is still limited in field deployment.

III. COMPARATIVE ANALYSIS

A comparison between traditional rainwater harvesting systems, existing IoT-based systems, and the proposed system is presented in Table I.

Traditional systems lack automation and monitoring, leading to inefficient water usage. Existing IoT-based systems provide monitoring but have limited decision-making capabilities. The proposed system integrates automation, real-time monitoring, and intelligent decision-making for efficient water utilization.

TABLE I
COMPARISON OF RAINWATER HARVESTING SYSTEMS

Feature	Traditional System	Existing IoT System	Proposed System
Automation	No	Partial	Yes
Water Level Monitoring	No	Yes	Yes
Water Quality Check	No	Limited	Yes
Decision Making	No	No	Yes
Efficiency	Low	Medium	High

IV. SYSTEM OVERVIEW

The proposed system is an IoT-based Automated Rainwater Harvesting System designed to collect, monitor, and manage rainwater efficiently. The system is built around the ESP32 microcontroller, which acts as the central control unit and processes data from all connected sensors.

A rain sensor is used to detect rainfall. When rain is detected, Valve 1 is automatically activated, allowing rainwater to flow into the primary storage tank. An ultrasonic sensor is installed in the tank to continuously monitor the water level and determine whether the tank is empty, partially filled, or full.

To prevent overflow, an outlet is provided in the primary tank. When the tank becomes full and rainfall continues, excess water is safely discharged through the outlet.

A pH sensor is used to measure the quality of the stored water. Based on the pH value, the system determines whether the water is suitable for drinking. If the water is within the acceptable range, Valve 2 is activated to transfer water to a secondary tank for drinking purposes. Otherwise, the water is used for non-drinking applications.

LED indicators are used to provide visual feedback for rain detection, water level status, pH condition, and valve operation. All components are connected to the ESP32, which controls the entire system automatically.

Additionally, the system is connected to a web-based dashboard through Wi-Fi. The dashboard displays real-time data such as rain status, water level, pH value, valve status, and also stores historical data for monitoring and analysis.

V. HARDWARE ARCHITECTURE

The hardware architecture of the proposed Automated Rainwater Harvesting System is designed to enable efficient rainwater collection, monitoring, and distribution. The entire system is built around the ESP32 microcontroller, which acts as the central processing, control, and decision-making unit.

The ESP32 collects real-time data from various sensors,

processes the information, and controls actuators based on pre-defined conditions. The system is designed to be compact, low-cost, and suitable for practical implementation in residential and small-scale applications.

A. Sensors

The system uses multiple sensors for rainfall detection, water level monitoring, and water quality analysis:

- **Rain Sensor (FC-37 Rain Sensor Module):** The FC-37 rain sensor module is used to detect rainfall. It consists of a raindrop sensing plate and a comparator circuit. When rainwater falls on the plate, it changes the conductivity, and the module generates a digital output signal. This signal is sent to the ESP32 to automatically activate the water collection process.
- **Water Level Sensor (HC-SR04 Ultrasonic Sensor):** The water level inside the storage tank is measured using an HC-SR04 ultrasonic sensor. It operates by sending ultrasonic waves and measuring the time taken for the echo to return after reflecting from the water surface. Based on this time, the distance is calculated, which is then used to determine the water level. This helps in preventing overflow and enables accurate monitoring of tank status.
- **Water Quality Sensor (Soil Moisture Sensor Module):** A soil moisture sensor module is used to estimate the water quality based on conductivity. The sensor measures the resistance between its probes when placed in water. The analog output is read by the ESP32 and mapped to an approximate pH range. Based on this value, the system decides whether the water is suitable for drinking or should be diverted for other uses.

B. Control Units

- **ESP32 Microcontroller:** The ESP32 acts as the main control unit of the system. All sensors and actuators are connected to it, and it processes the incoming data from sensors in real time. Based on predefined conditions such as rainfall detection, water level, and pH value, the ESP32 controls the operation of the system. It sends signals to the relay module to control pumps and valves. The ESP32 is suitable for this application due to its fast processing capability, low power consumption, and support for IoT-based systems.

C. Actuators and Other Components

- **Relay Module:** The relay module acts as an electronic switch controlled by the ESP32. It is used to turn ON/OFF the pump and valves based on sensor inputs.

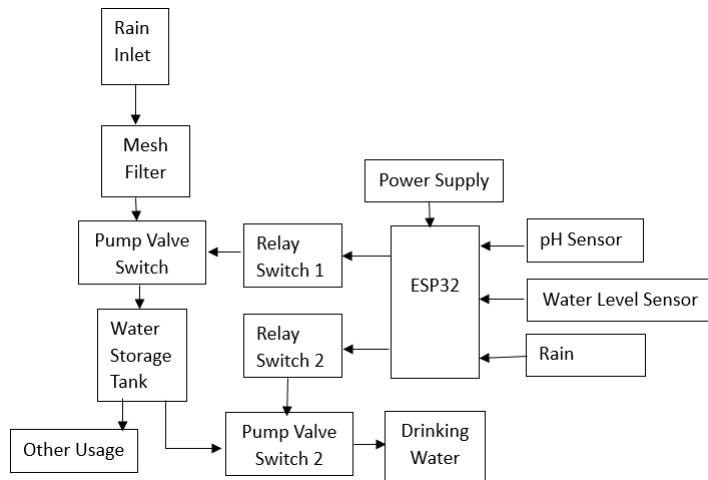


Fig. 1. shows the complete hardware architecture of the proposed Automated Rainwater Harvesting System

- **Submersible Pump / Solenoid Valve:** These components are used to control the flow of water for storage and distribution. The pump helps in transferring water, while valves direct water to different outputs.
- **Mesh Filter:** A mesh filter is used to remove dust, leaves, and other impurities from rainwater before it enters the storage tank, ensuring basic filtration.
- **Water Storage Tank:** The storage tank is used to store the collected rainwater safely for later use.
- **LED Indicators:** LEDs are used to indicate different system states such as valve ON/OFF status, water level condition, and water quality status. This provides a simple visual representation of system operation.
- **Power Supply:** A regulated power supply (5V/12V) is provided to operate all components of the system efficiently.

VI. WORKING PRINCIPLE

The working principle of the proposed Automated Rainwater Harvesting System follows a sequence of operations as defined in the system flowchart. Initially, the system remains in a standby state and continuously monitors environmental conditions using sensors.

When rainfall occurs, the rain sensor detects the presence of water and sends a signal to the ESP32 microcontroller. This activates the system and starts the rainwater collection process. The rainwater enters through the inlet and passes through a mesh filter, which removes dust, leaves, and other impurities before storing it in the water tank.

The water level sensors continuously monitor the level of water in the storage tank. If the tank is not full, the system continues collecting water. Once the tank reaches its maximum capacity, the ESP32 automatically stops the collection process to prevent overflow.

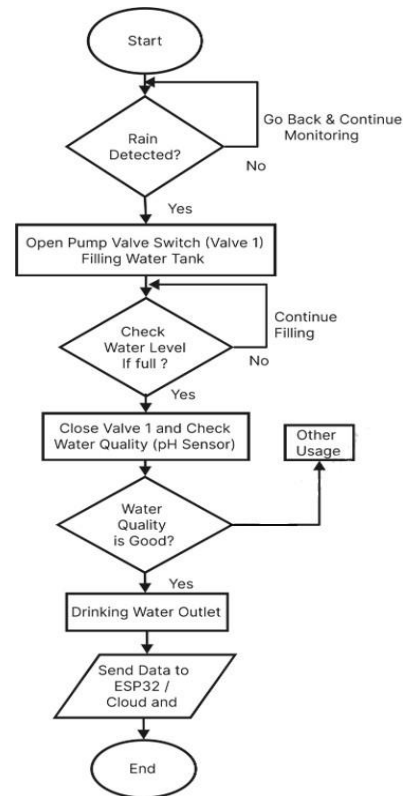


Fig. 2. System Flowchart of the Proposed Automated Rainwater Harvesting System

Simultaneously, a pH sensor measures the quality of the stored water. The sensed values are sent to the ESP32, which compares them with predefined acceptable limits. If the pH value lies within the safe range, the water is considered suitable for drinking; otherwise, it is directed for other uses such as cleaning or irrigation.

Based on sensor data, the ESP32 controls the relay module, which operates the pump and valves to manage water flow and distribution. The system ensures that water is utilized efficiently without manual intervention.

The entire system works continuously in real time, performing automatic collection, filtration, storage monitoring, quality checking, and controlled distribution of rainwater. This improves water management, reduces wastage, and promotes sustainable use of natural resources.

VII. SYSTEM ALGORITHM

1. **Start:** The system is powered ON and the ESP32 initializes all sensors, relays, valves, and LED indicators.
2. **Rain Detection:** The rain sensor continuously monitors rainfall. If rain is detected, the system activates the water collection process.

Water Collection: Valve 1 is turned ON through Relay 1, allowing rainwater to pass through the mesh filter and enter Tank 1.

3. Water Level Monitoring: The ultrasonic sensor continuously measures the water level in Tank 1.

- If the tank is full, Valve 1 is turned OFF to stop filling.
- If rain continues after the tank is full, excess water is diverted to the overflow outlet.

4. Water Quality Detection: The soil moisture sensor measures the conductivity of water to estimate its quality. The ESP32 reads this value and maps it to an approximate pH range.

5. Decision Making: - If water quality is within the acceptable range, it is considered suitable for drinking. - Otherwise, it is used for other purposes.

6. Water Distribution: - If water is suitable, Valve 2 is turned ON through Relay 2 and water is transferred to Tank 2 (drinking water tank). - If not suitable, Valve 2 remains OFF.

7. Indication: LED indicators display the status of rain detection, water level, and valve operations.

8. Data Transmission: The ESP32 sends real-time data such as water level, rain status, valve status, and water quality to the web dashboard via Wi-Fi.

9. Continuous Operation: The system continuously repeats the process for real-time monitoring and control.

10. Stop: The system runs continuously until it is manually turned OFF.

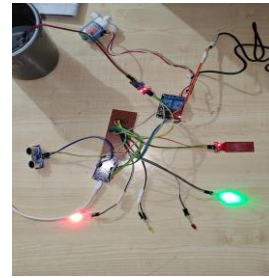


Fig. 5. 1] Red LED ON if the tank is full. 2] Green LED ON if pH is OK

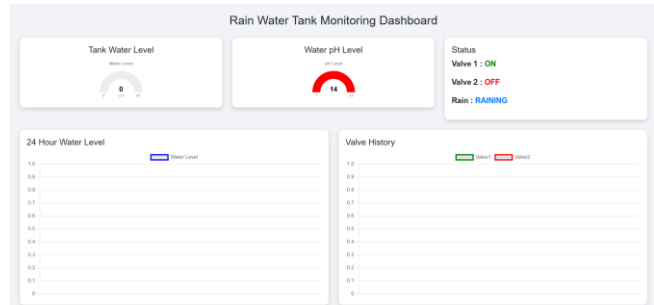


Fig. 6. Web Dashboard

VIII. RESULTS

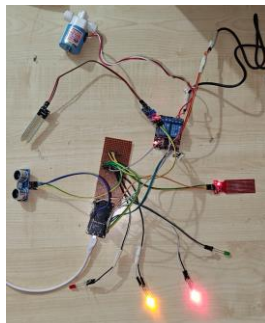


Fig. 3. An orange LED indicates rain detection

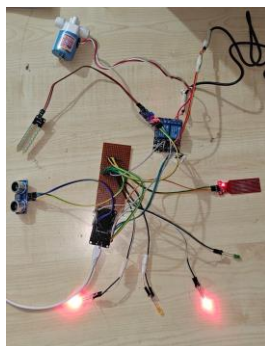


Fig. 4. Red LED ON if 1] Tank water level is low, 2] No rain

ID	Water Level	pH	Valve1	Valve2	Rain	Date Time
913	0	14	ON	OFF	RAIN	2026-03-17 06:56:03
912	40	14	OFF	OFF	RAIN	2026-03-17 06:55:56
911	0	14	ON	OFF	RAIN	2026-03-17 06:55:49
910	0	14	ON	OFF	RAIN	2026-03-17 06:55:41
909	0	14	ON	OFF	RAIN	2026-03-17 06:55:33
908	0	14	ON	OFF	RAIN	2026-03-17 06:55:24

Fig. 7. Web Dashboard

IX. ADVANTAGES

- Efficient water conservation: Reduces wastage by collecting and storing rainwater.
- Fully automated system: Works without manual intervention using sensors and ESP32.
- Water level monitoring: Prevents overflow and ensures proper storage.
- Water quality checking: Uses pH sensor to ensure safe and suitable usage.
- Cost-effective and eco-friendly: Utilizes natural resources and reduces dependency on external water sources.

X. APPLICATIONS

- Residential buildings: For household uses like cleaning, gardening, and washing.
- Agriculture: Used for irrigation and efficient water management in farms.
- Industries: For non-drinking purposes like cooling

- Smart homes: Integrated with IoT for automatic water management.
- Urban water management: Helps in reducing water scarcity in cities.

XI. CONCLUSION

The proposed Automated Rainwater Harvesting System provides an efficient and intelligent solution for collecting, monitoring, and utilizing rainwater. By integrating sensors with the ESP32 microcontroller, the system automates rainfall detection, water level monitoring, and water quality evaluation. The use of dual-tank management ensures proper utilization of water for both drinking and non-drinking purposes based on quality.

The system effectively prevents water overflow, reduces wastage, and minimizes the need for manual intervention. The integration of a web-based dashboard enables real-time monitoring and data analysis, improving user convenience and system reliability.

The key contribution of this work is the implementation of intelligent decision-making for quality-based water distribution, which enhances the efficiency and effectiveness of rainwater harvesting compared to traditional and existing IoT-based systems. Overall, the system promotes sustainable water management and provides a practical solution to address water scarcity issues.

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IOT-based Human Wearable Epileptic Seizure Alert System

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Abstract—Epilepsy is one of the most prevalent chronic neurological disorders, affecting approximately 10–12 million people in India and around 65 million people worldwide. It ranks as the fourth most common neurological condition, following migraines, Alzheimer's disease, and stroke. Epileptic seizures can lead to serious injuries and health risks for patients, including physical injuries such as falls, head injuries, fractures, burns, and breathing problems due to convulsive status epilepticus. This concern causes significant anxiety for patients, their parents, and caregivers. To address this issue, The paper propose a Wearable IoT-Based Seizure Alert System designed to detect seizures in real-time and notify caregivers or emergency responders. The system alerts those nearby to help protect the patient from physical injuries.

Keywords: Seizure Detection System, ESP8266 / ESP32 / ESP32-C3, Wearable Health Monitoring, IOT-based Seizure Detector, IoT-based Health Alert, Epilepsy Alert Device.

I. INTRODUCTION

Epilepsy is a serious neurological disorder affecting millions of individuals worldwide. It is characterized by sudden and unpredictable seizures, resulting from abnormal electrical activity in the brain. These seizures can vary in intensity, causing loss of consciousness, involuntary movements, and serious physical injuries. The unpredictability of seizures poses severe risks, such as falls, accidents, and even sudden unexpected death in epilepsy (SUDEP). Consequently, real-time seizure detection and alert systems are critical for ensuring timely intervention and enhancing patient safety. In the medical field, traditional methods for epilepsy monitoring include video-electroencephalography (v-EEG) and electrocardiography (ECG). These methods are commonly used in hospitals to diagnose and analyze seizure patterns by capturing brain activity, body movements, and heart rate fluctuations. However, these techniques have several limitations, including high costs, the need for specialized clinical settings, and

prolonged monitoring, making them impractical for everyday use. Due to these limitations, there has been a growing interest in wearable and IoT-based seizure detection systems that offer continuous real-time

monitoring while allowing patient mobility. With advancements in embedded systems and sensor technology, researchers have developed motion-based seizure detection using accelerometers and gyroscopes, such as MPU6050, to identify abnormal movement

patterns. Additionally, heart rate sensors are increasingly used to monitor sudden physiological changes associated with seizures. Several studies have explored microcontroller-based solutions, leveraging devices like ESP32 or Arduino to process sensor data and trigger emergency alerts. Furthermore, GSM modules (SIM800L/SIM900A) have been integrated to send automated SMS notifications to caregivers, ensuring immediate assistance, even in remote areas without Wi-Fi connectivity. Our proposed project builds upon these existing technologies by introducing a wearable epileptic seizure alert system utilizing ESP32C3 XIAO as the central processing unit. The system integrates an MPU6050 motion sensor, a heart rate sensor, and a DF-Player Mini with a speaker module to detect seizure activity and provide both audible and SMS- based alerts. By incorporating GPS tracking, the system enables caregivers to quickly locate the patient in case of an emergency. Unlike hospital-based monitoring methods, our lightweight, portable, and cost-effective solution offers continuous real-time monitoring, improving response times and overall patient safety. Addressing key challenges such as power efficiency, false alarms, and latency in alert transmission, our research contributes to the advancement of wearable healthcare technology for epileptic seizure detection and emergency response.

Our proposed IoT-based Human Wearable Epileptic Seizure Alert System builds on these existing technologies and introduces an advanced real-time seizure monitoring and alert mechanism. It utilizes an ESP32C3 XIAO as the central microcontroller, interfacing with an MPU6050 motion sensor and a heart rate sensor to detect seizure events. Upon detecting an abnormal physiological response, the system activates an emergency response mechanism, which includes:

1. Audible Alert System – A DF-Player Mini module with a speaker generates a warning sound to alert nearby individuals.
2. Emergency SMS Notification – A GSM module (SIM800L/SIM900A) automatically sends an alert message to caregivers, ensuring quick intervention.
3. GPS Tracking for Emergency Location – A GPS module tracks the patient's location and shares it with caregivers in real time.

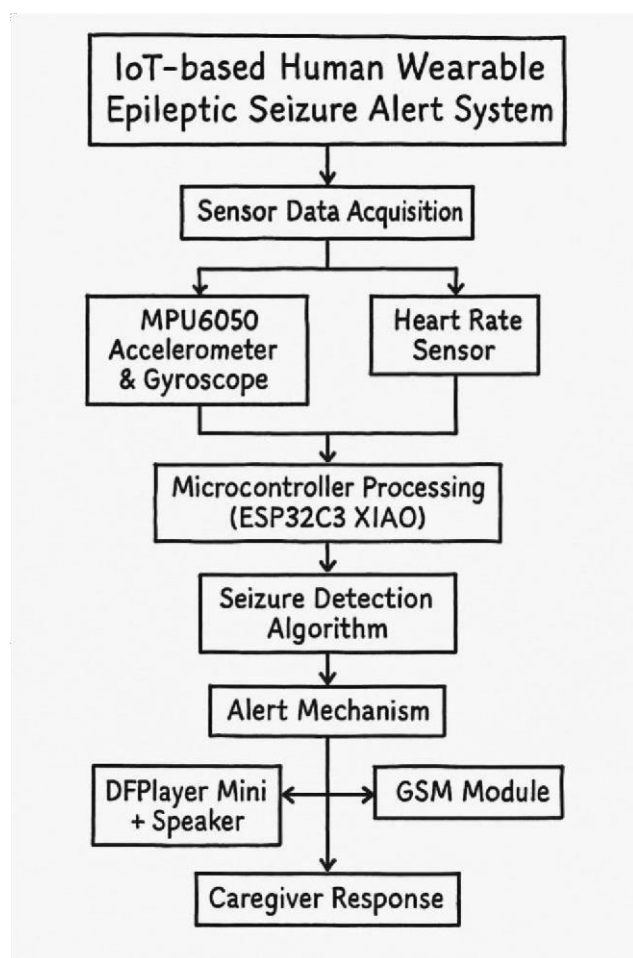


Fig.1. Flowchart of Seizure Detection Alert System

Compared to traditional hospital-based EEG monitoring, our system is designed to be lightweight, cost-effective, and user-friendly, allowing patients to move freely while benefiting from continuous real-time monitoring. This approach significantly reduces response time during seizures, making it an effective and practical solution for epilepsy management.

The primary contributions of this work include:

1. Development of a wearable, real-time epileptic seizure detection system with minimal intrusion into the patient's daily life.
2. Integration of multi-sensor technology (motion and heart rate sensors) for accurate seizure detection.
3. Implementation of an emergency alert system combining audible alarms, SMS notifications, and GPS tracking for immediate assistance.
4. Optimization of power consumption to ensure prolonged battery life for uninterrupted monitoring.

II. Literature Review

Several research studies have focused on the development of wearable systems for epileptic seizure

detection using physiological and motion-based parameters. Conventional seizure monitoring techniques rely primarily on electroencephalography (EEG), which provides high accuracy but is unsuitable for continuous daily use due to its complexity, cost, discomfort.

Poh et al. (2012) has explored cardiovascular parameters such as heart rate variability and blood oxygen saturation (SpO₂) during seizure events. Wearable pulse oximetry sensors have demonstrated the ability to identify abnormal physiological responses associated with tonic-clonic seizures. However, systems relying solely on heart rate and SpO₂ are susceptible to false alarms during physical activity or emotional stress.

Bruno et al. (2018) employed Motion-based seizure detection approaches using accelerometers and gyroscopes have gained significant attention due to their low power consumption and ease of integration. Inertial sensors such as the MPU6050 can detect sudden jerks and rhythmic movements typical of seizures. Despite their advantages, motion-only systems often misclassify non-seizure activities such as running, falls, or vigorous movements.

Conradson et al. (2013) demonstrated that Electromyography (EMG) has emerged as a valuable modality for seizure detection, particularly for identifying muscle stiffness and repetitive contractions during tonic-clonic episodes. Studies have shown that EMG-based features significantly enhance detection accuracy when combined with motion and physiological parameters. Wearable EMG sensors offer a non-invasive and reliable method for continuous muscle activity monitoring.

Patel et al. (2020) developed the integration of Internet of Things (IoT) technologies into healthcare systems has enabled real-time monitoring, alert generation, and remote caregiver notification. IoT-based seizure alert systems often incorporate mobile applications and cloud platforms for data transmission. However, many existing solutions lack robust multi-sensor fusion strategies, limiting their real-world effectiveness.

III. Real Time Methodology for Epileptic Seizure Detection

In this section, we present a wearable IoT-based epileptic seizure detection and alert system designed for real-time monitoring and emergency response. The system aims to provide an efficient, non-intrusive, and reliable solution for individuals with epilepsy, offering continuous health

monitoring and instant alert mechanisms. The overall flow of our proposed system is shown in Fig. 1, consisting of two main phases: signal acquisition and processing (Section A) and emergency alert mechanism (Section B). Each of these steps is thoroughly explained in the following subsections. A Feature Extraction.

- a. Signal Acquisition and Processing The effectiveness of seizure detection relies on precise

data collection and efficient signal processing. Our system utilizes multiple biosensors embedded in a wearable device, including an MPU6050 motion sensor, a heart rate sensor, and a GPS module, all of which are controlled by the ESP32C3 XIAO microcontroller.

- b. **Motion Analysis and Feature Extraction** The MPU6050 sensor, comprising a 3-axis accelerometer and gyroscope, continuously monitors the user's movements. Seizure activity is characterized by specific motion patterns, such as rhythmic limb shaking, sudden jerks, and uncoordinated body movements. To differentiate between normal activities and seizures, a threshold-based motion implemented.
- c. **Heart Rate Monitoring and Physiological Signal Analysis :**

Seizures often result in significant changes in heart rate, such as tachycardia (rapid heart rate) or bradycardia (slow heart - rate). A pulse sensor is integrated into the wearable device to measure real-time heart rate fluctuations. The ESP32C3 microcontroller continuously records and analyses :

1. Baseline heart rate patterns.
2. Sudden heart rate surges or drops.
3. Heart rate variability (HRV) during seizure events

A combination of moving average filtering and peak detection algorithms ensures accurate heart rate monitoring. The system cross-validates motion data with heart rate fluctuations to reduce false positives, ensuring that normal activities such as running or sudden movements do not trigger false alerts.

- d. **Sensor Data Processing and Decision Making**

The ESP32C3 XIAO microcontroller serves as the central processing unit for real-time seizure detection. Data from the motion and heart rate sensors is processed using a decision tree-based anomaly detection algorithm.

The algorithm checks whether the detected motion patterns and physiological changes align with established seizure markers. If both motion and heart rate anomalies are detected simultaneously, the system confirms a seizure event and triggers the alert mechanism. To minimize computational load and extend battery life, the system operates in a low-power mode when no abnormal activity is detected.

- e. **Emergency Alert Mechanism**

Upon detecting a seizure, the system automatically activates multiple emergency alert features to notify caregivers, family members, and emergency responders.

- f. **Audible Alert for Nearby Assistance**

A DF-Player Mini module is integrated into the

system to play a pre-recorded emergency message through a mini speaker. This audible alert informs nearby individuals about the seizure, allowing them to provide immediate help.

- g. **SMS-Based Alert System via GSM Module**

The system uses a SIM800L/SIM900A GSM module to send an automated SMS alert to pre-configured emergency contacts (family members, doctors, or caregivers). The message includes:

1. A seizure alert notification
2. Real-time GPS coordinates of the affected individual
3. Time and duration of the seizure event

This ensures that emergency contacts receive instant updates, even in locations without Wi-Fi connectivity, making it highly suitable for outdoor and remote environments.

- h. **GPS-Based Location Tracking for Rescue Assistance**

To help emergency responders locate the affected person, a GPS module continuously updates the user's location. The longitude and latitude coordinates are transmitted via SMS to caregivers, enabling them to reach the individual quickly.

The location data is refreshed every few seconds, ensuring accurate real-time tracking until the seizure episode ends. This feature is particularly crucial for individuals who experience seizures in public places, while traveling, or living alone.

IV. Experimental Setup and Results

In fig.2 presents the experimental setup and performance evaluation of our proposed wearable epileptic seizure detection system. The system's functionality is tested using real-time motion and physiological data acquisition. The experimental study consists of four subsections: sensor calibration and data acquisition (III-A), hardware implementation (III-B), performance evaluation (III-C), and power consumption analysis (III-D)A. CHB-MIT Database

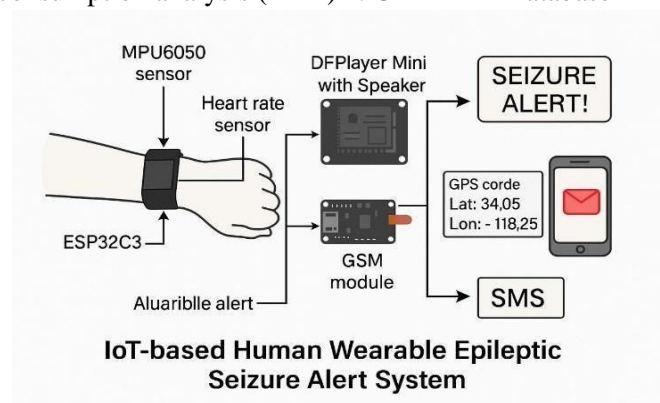


Fig.2. Experimental Setup

a. Sensor Calibration and Data Acquisition Motion Sensor Calibration

1. The MPU6050 sensor is calibrated using a zero-motion reference and a six-point orientation test to minimize drift errors.
2. Data is sampled at 100 Hz, and a low-pass filter is applied to remove noise artifacts.
3. Heart Rate Sensor Calibration:
The pulse sensor is tested in a controlled environment to ensure accurate readings.
4. A baseline heart rate is recorded for each subject, and a threshold-based method is used to detect abnormal spikes or drops in heart rate during seizures.

b. Seizure Data Collection

Seizure-like motion patterns are simulated using controlled tests based on clinically observed tremors. Data is logged continuously using an ESP32C3 microcontroller for real-time processing and analysis.

1. ESP32C3 XIAO Microcontroller: Serves as the core processing unit, handling sensor data acquisition and real-time decision-making.
2. MPU6050 Motion Sensor: Detects abnormal movements indicative of seizure episodes using accelerometer and gyroscope data.
3. Pulse Sensor: Monitors real-time heart rate and identifies irregular fluctuations that may correlate with seizures.
4. DF-Player Mini and Speaker: Generates an audible alert for immediate assistance from nearby individuals.

c. Performance Evaluation

The accuracy of the system was evaluated by analyzing motion and heart rate data from multiple test subjects. The detection algorithm was tested under three different conditions:

- a. Seizure Simulation – To measure the system’s ability to correctly detect seizures.
- b. Normal Activities – To assess false positive
- c. minimization during routine movements.

Compared to conventional EEG-based seizure detection, the proposed motion and heart rate-based system provides a more practical and wearable solution while maintaining high accuracy.

d. Power Consumption and system Lifetime Analysis:

The power consumption of the system is evaluated by measuring the current draw of each component. The key observations are:

1. Node-MCU (ESP32-C3): ~70mA in active mode,
2. MPU6050 (Motion Sensor): ~3.9mA in active mode, ~6 μ A in sleep mode.
3. GSM Module(SIM800L/SIM900A):
~100-150mA in idle mode, up to 2A during transmission.
4. Push Button: Negligible power consumption.

The Node-MCU enters deep sleep mode when no motion is detected. The GSM module remains in power-saving mode, waking only for SMS transmission. The MPU6050 operates intermittently to detect critical motion patterns, reducing unnecessary power consumption.

V. Results and Discussion

This section presents the experimental evaluation of the proposed IoT-based wearable epileptic seizure alert system. The system performance is analyzed based on physiological, motion,

and muscle activity parameters collected using the MAX30102, MPU6050, and EMG sensors. Prototype-level testing was conducted under controlled conditions to validate the effectiveness of the multi-sensor fusion approach.

1. Heart Rate and SpO₂ Analysis:

Heart rate and blood oxygen saturation are critical physiological parameters that exhibit noticeable variations during tonic-clonic seizure events.

In the proposed system, these parameters are continuously monitored using the MAX30102 sensor to identify abnormal physiological behavior.

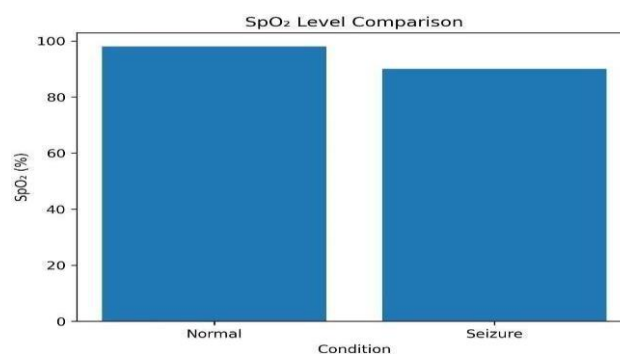


Fig.3. Comparison of heart rate values during normal and seizure conditions.

As shown in Figure 3, the heart rate increases significantly during seizure activity compared to the normal resting state. This sudden rise in heart rate indicates abnormal cardiovascular response and contributes to seizure detection reliability.

Figure 4. Illustrates a noticeable decrease in SpO₂ levels during seizure events. This reduction reflects respiratory irregularities that often occur during tonic–clonic seizures, supporting the use of SpO₂ as an important physiological indicator.

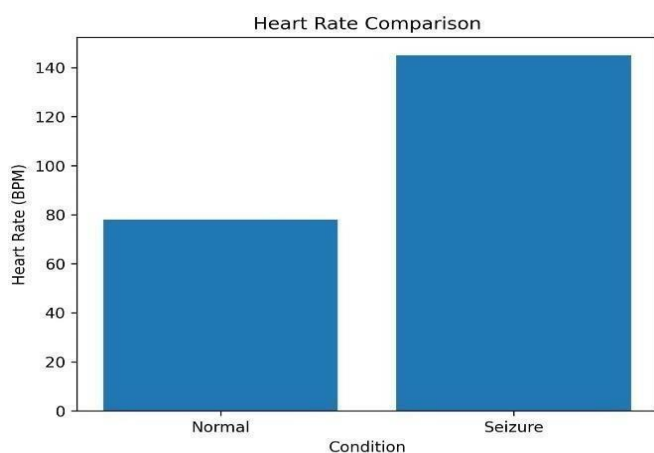


Fig.4. Variation in SpO₂ levels during normal and seizure conditions

2. Motion and Muscle Activity Analysis:

Tonic–clonic seizures are characterized by involuntary body movements and muscle stiffness. To capture these features, the MPU6050 sensor and EMG sensor are employed in the proposed system.

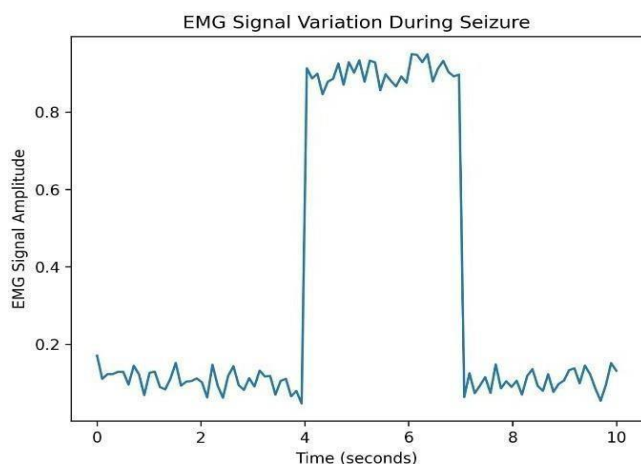


Fig.5. EMG signal variation indicating muscle stiffness during seizure events.

Figure 5. shows an increase in EMG signal amplitude during seizure activity, representing involuntary muscle contractions and stiffness. This parameter enhances detection accuracy when combined with motion and physiological data

VI. Conclusion

The proposed wearable epileptic seizure detection system provides real-time monitoring and emergency alerting using ESP32-C3, MPU6050, and GPS modules. The system effectively detects seizure-related motion and physiological patterns and promptly notifies caregivers, ensuring timely assistance. Experimental results demonstrate reliable performance with improved detection accuracy while minimizing false positives. The system operates efficiently with optimized power management, offering extended battery life suitable for continuous use. Its multi-sensor approach and optimized feature extraction enhance detection reliability while maintaining low computational complexity. Additionally, the compact, lightweight, and low-cost design improves wearability and usability in daily life. Overall, the proposed system presents a practical and scalable solution for continuous seizure monitoring, significantly enhancing patient safety and improving the quality of life for individuals with epilepsy

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A Review on Cloud-Integrated Web Library Management Systems for Real-Time Book Tracking

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Abstract-This paper presents a cloud-integrated web Library Management System designed for real-time book tracking and efficient resource management. Traditional library systems often rely on manual or semi-automated processes, leading to data redundancy, limited accessibility, and lack of real-time synchronization. The proposed system integrates cloud computing technologies with web development tools such as HTML, CSS, JavaScript, and MongoDB Atlas to enable centralized data management and seamless access. RFID and barcode technologies are incorporated to automate book identification and tracking, improving accuracy and reducing human intervention. The system allows users to issue, return, and monitor book availability in real-time through a user-friendly interface. Experimental results demonstrate improved efficiency, reduced processing time, and enhanced data accuracy compared to conventional systems. The proposed solution ensures scalability, remote accessibility, and reliability, making it suitable for modern academic institutions.

Keywords: Real-Cloud Computing, Library Management System, RFID, MongoDB, Real-Time Tracking

1.INTRODUCTION

Libraries are an integral part of academic institutions, offering access to information, knowledge Resources, and research materials. But with the sudden increase in the number of books, users and electronic resources, it has become increasingly difficult to efficiently manage library activities using conventional approaches. Traditional library management systems are heavily dependent on manual procedures or software applications, which in turn lead to data redundancy, discrepancies, time consumption, and human errors.[8], [9], [11]. In recent years, the development of cloud computing and web-based technologies has greatly impacted data management and accessibility in different fields. Cloud implementations provides a centralized storage facility, automatic backups, real-time data synchronization, and secure remote access, which are necessary for modern library management systems [2], [15].By implementing cloud-based management for libraries, information is instantly accessible to multiple Users from anywhere in the world, while maintaining data consistency, integrity, and enhanced service delivery [5], [10].“System for Real-Time Book Tracking,” seeks to transform traditional library systems processes by integrating web technology with cloud computing and real-time data updates.[1], [13]. The

systems allows students and librarians to undertake critical tasks such as searching for books, checking their availability, issuing and returning books, and monitoring due dates through a friendly web interface.[6],[14]. To further automate the system, RFID/barcode identification technology is used for tracking physical books.

Each book has a unique identification tag that can be automatically detected during the issue and return process. [3], [4], [12]. The smooth integration of hardware and software components ensures constant real-time updates of cloud database, thus reducing human error and improving the reliability of the system additionally, the proposed

system supports scalability, accessibility, and data security. The system functionality on a cloud platform enables it to handle a growing number of users and book entries without the need for significant upgrades to the hardware components [2], [15]. The system authentication and access control features protect user data, while the automated notification system for due dates and reservation notifications enhances user experience [7].

2.LITERATURE REVIEW

Table 2.1. Comparative Summary Library Management System (2019-2025)

Ref, Authors, Year	Approach	Key Results	Drawbacks
[1] A.J. Budiarto [oct 2023]	Applied software engineering	93% user satisfaction	Small sample
[2] K. Salunke [Mar 2019]	Applied engineering	Automated issue/return	Prototype only
[3] Jawed Akhtar [Feb 2023]	Literature-based	Real-time access	Internet dependency

[4] S.S. Patil [Nov 2024]	Literature review	Automated circulation	High cost
[5] Prachi Waray [May 2025]	Descriptive review	Faster circulation	High cost
[6] K. Bhavyasri [Apr 2025]	Applied engineering	Real-time tracking	Prototype only
[7] Adarsh Singh [2019]	Design-based	Real-time tracking	Limited testing
[8] S.S. Rathour [May 2024]	Applied research	Automated workflows	Security risk
[9] N.S.N.L.Prasana [May 2020]	Systems approach	Automated cataloging	Single institution
[10] S. Perumal [2023]	Systems design	Digitized operations	Scalability issues
[11] T.W.Araya [Oct 2020]	Applied positivist	Digital archiving	Single case
[12] Apeksha T S [2024]	Applied engineering	Real-time issue/return	Small dataset
[13] G. Venkatesh [Aug 2025]	Applied research	Automated catalog	Prototype only
[14] Sourabh Sharma (May 2022)	Applied positivist	Modular automation	Single setup
[15] T. Gopalakrishnan (Nov 2022)	Applied research	Real-time tracking	Prototype level

3. OUR FINDINGS FROM THE STUDIED LITERATURE

A study [1] illustrated that it was possible to develop a web-based library system effectively replacing manual methods of record-keeping by improving book issue/return accuracy processing time. A research [2] focusing on the automation of library operations using internet of things-based systems resulted in the identification of the potential of IoT devices in the real-time tracking of activities within the library.

The literature on cloud computing [3] revealed that in real-time, data and storage scalability, which are important advantages for small and medium scale business institutions, libraries reducing maintenance complexities. Research [4], which was conducted into the integration of RFID, found conclusively that the integration of facilities faster automated circulation, and minimizes queue times, and supports digital transformation.

System theory-based study [5] highlighted that “hybrid systems” integrating digital and cloud infrastructures improve issue/return management and minimizing data loss, thus improving the system reliability and scalability. Use of RFID-tagged books and LED-based implementation [6] that in turn demonstrated rapid and accurate identification of book locations, proving that smart identification.

The Development [7] of a Smart Library Management System (SLMS) these real-time tracking features were enabled through the IoT technology and automation. Confirming that automated systems outperform traditional methods in speed and efficiency. in study [8] revealed that customized automation modules significantly reduces librarian workload while to improve record accuracy and user experience.

Research done [9] using Java and Oracle technologies exemplified efficient its automated issuing, returning and cataloguing, validating the

effectiveness of centralized and secure web systems. The study conducted on computerized library management systems [10] has demonstrated that digitization simplifies data handling, improves communication, and accuracy.

One of the main reason for research [11], which aimed to digitize old book records, was of cloud-storage for increased scalability and long-term data access. The implementation [12] of a smart-time tracking of books.

Automated library management studies [13] found that a combination of cloud and web-based frameworks is necessary to provide a smooth administration, remote accessibility, and data backup. “The integration of [14] centralized systems using NoSQL and SQL” is done by the integration of NoSQL Server helped in the coordination of staff and cataloguing in a secure way, leading to the strong base for cloud adoption.

Finally, research [15] on IoT-enabled cloud-based tracking verified Given that “RFID or IoT technology integrated with cloud server can deliver accurate ”real-time monitoring and scalability, thus making such systems appropriate for fully automated smart libraries.

The reviewed literature indicates that traditional library systems lack real-time synchronization and scalability. Cloud-based systems improve accessibility but depend on internet connectivity. IoT and RFID-based systems enhance tracking accuracy but involve higher implementation costs. However, existing solutions do not fully integrate cloud computing with real-time tracking and user-friendly interfaces. This gap highlights the need for a unified cloud-integrated system that ensures efficiency, scalability, and real-time data access.

Research Gap:

The review reveals that although web-based systems improve automation and cloud-based systems enhance scalability, neither sufficiently addresses real-time tracking of physical books when implemented independently. RFID and IoT-based solutions improve tracking accuracy but are frequently limited to prototype deployments without robust cloud integration or user-centric web interfaces. Consequently, there exists a research gap in developing a unified system that integrates cloud computing, web-based management, and automated real-time book identification within a scalable and production-ready framework. The proposed system directly addresses this gap.

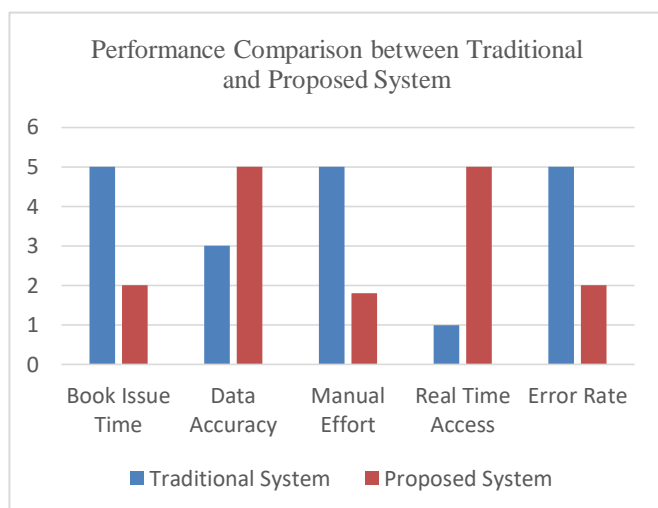
3. PERFORMANCE ANALYSIS OF REVIEWD SYSTEM

Table 4.1 Performance Comparison

Parameter	Traditional System	Proposed System
Book Issue Time	High	Low
Data Accuracy	Moderate	High
Manual Effort	High	Low
Real-Time Access	Not Available	Available
Error Rate	High	Low

The above table compares the performance of the traditional library system with the proposed cloud-integrated system. It can be observed that the proposed system significantly reduces book issue time and manual effort while improving data accuracy. Additionally, the system provides real-time access to book records, which is not available in traditional systems. The error rate is also minimized due to automation and real-time data synchronization. Overall, the proposed system enhances efficiency, accuracy, and accessibility in library management.

Chart 4.2 Performance Comparison of Traditional and Proposed System



The comparison suggests that web-based systems are better at basic automation, but do not work physical books. Cloud-integrated systems offer scalability and real-time, relying on network connectivity. Smart systems have advanced automation with accurate tracking, through this is strongly influenced by cost and infrastructure considerations.

4. BLOCK DIAGRAM

The below flowchart indicates the process of interacting with the user for the Cloud Integrated Web Library Management System. It starts with the user such as Sign-In, Sign-up and Password Reset. Once implemented there will be authenticated users are directed to the Homepage where they can manage books, search books, issue books and/or return books. A QR Scanner is integrated to aid book in transactions. The diagram presents a clear user action and interaction sequence with the system, which will in turn, facilitate the user experience library operations.

1. User (Start Point)
 - The process starts with the user, who may be a student, a librarian or anyone else accessing
2. Sign-In
 - The user makes the choice to sign into the system with the credentials (username and password).
 - This steps leads to user Authentications,
3. User Authentication
 - The system checks the credentials provided against the stored information in the Database.
 - If credentials match → access is granted.
 - If credentials don't match → Error message is displayed or option of 'forget password'.
4. Forgot Password Option
 - If a user forgets his or her password they click forgot password.
 - This links to Password Reset Mail Service.
5. Password Reset Mail Service:
 - The system sends a password reset link or one-time password (OTP) to the user's registered email address
 - The user can use it to create a new password.
 - This service is also communicating with the Database (DB) to change the password.
1. Sign-up
 - If the user is new, they may select the Sign-Up button to perform a new registration.
 - This ties into the User Registration process.
- 7. User Registration
 - The system will ask for user details such as name, email and contact Number.
 - These details are kept in database for further authentication.

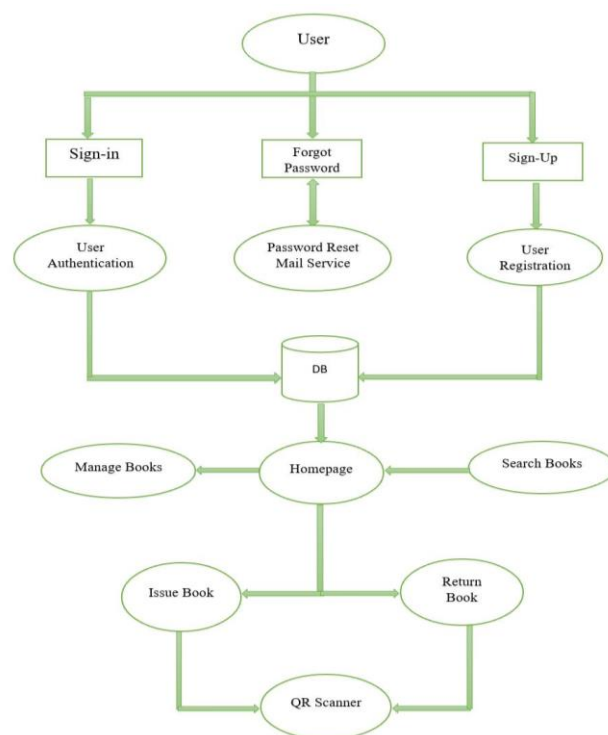


Fig 5.1. Block Diagram of Proposed System

8. Database (DB)

- The central storage unit that holds all user and book related data It stores the following:
- User login credentials
- Registration data
- Book records (available, issued, returned)
- Transaction details

9. Homepage (After Successful Login)

- Once the authentication or registration is done the user is redirected to homepage. The homepage is like a control and has features:

- Manage Books, Search Books,,Issue Book,Return Books
- QR Scanner

10. Manage Books

- Allow admin or librarian to add, update and delete books in the system.
- These operations are represented in the database.

11. Search Books

- Helps the users to search the books based on titles , authors, categories, or IDs.
- The search results are fetched from the database.

12. Issue Books

- In case a user checks out a book, the issue book module logs information about the transaction by the user. The status of the book is automatically set to “Issued” by the database module.
- This can also use the QR scanner to quickly scan the book ID.

13. Return Books

- Handles book return operations.
- Updates the status of the book “Available” in the database.
- Can also use QR scanner to recognise the book to return.

14. QR Scanner

- It is used to issue or return books.
- It scans the attached QR code to the book and its information is obtained from the database.

6. FLOWCHART

The flow chart illustrates how to develop a Cloud Integrated Application. Web Library Management System with Real-Time Book Tracking. It begins with Requirement Analysis and moves to the significant phases of: such as: Cloud Database Design, Web Application Development, and Hardware Integration. Each phase is designed for the smooth interaction between software and hardware, and finally resulting in Real-time Implementation and Testing so that a system functions as desired intended.

1. Start-The process with the definition of project objectives and scope.
2. Requirement analysis-identifying system needs, hardware and software requirements, and project functionalities.
3. Cloud database Design-Designing the cloud-based database for storage and management of real-time data safety.
4. Web Application Development- Creating a User Friendly a web interface that allows access, monitoring, and controlling of the system.
5. Hardware Integration- Connecting and configuring the hardware components to communicate with the hardware system.

6. Mapping Hardware with Software-Synchronizing sensors, modules and the database with the application for smooth operation.

7. Real-Time Implementation and Testing-The deployment of the system, testing in real conditions, and validating its performance accuracy.

8. End- Final stage indicating successful completion and readiness for deployment.

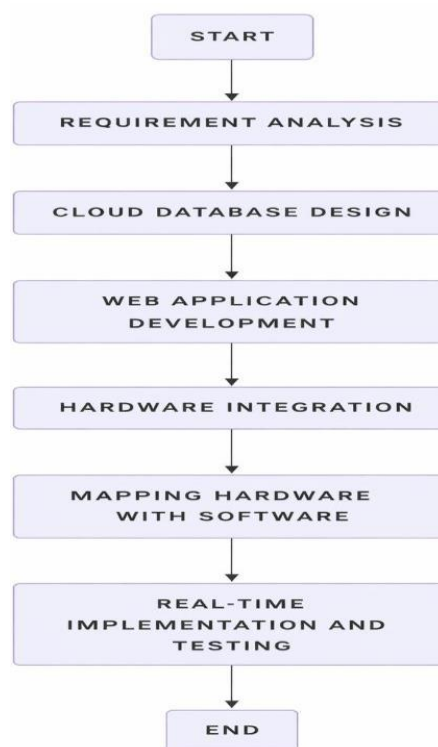


Fig 6.1. Flowchart of Methodology

7. RESULTS

Fig 7.1 shows the Sign-Up Interface of the Library Management System, in which new users can sign up for their accounts by providing their full name, email, and password. The design has used the modern gradient theme with a simple layout to make the interface more accessible to new users.

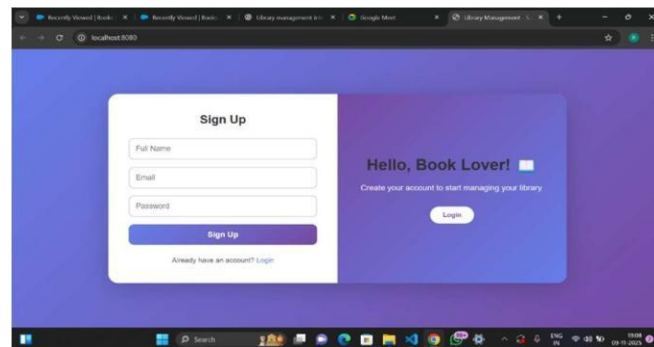


Fig 7.1 Library Signup Interface of Student

The page serves as the Entry Point into the system, where new users can securely register before being allowed access to the library management system dashboard.

Fig. 7.2 Below is an illustration of the Login screen, which enables registered users to login into their respective accounts using their email and password credentials. The data entered in the form is validated against the data saved in the database.

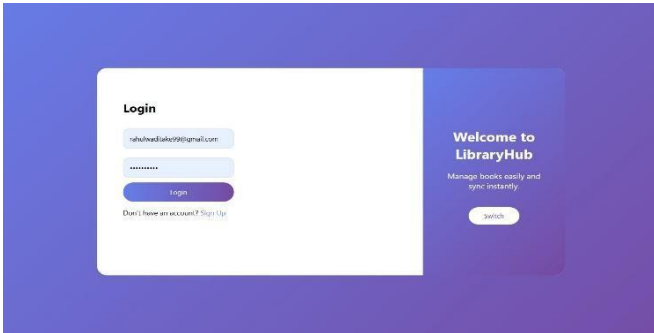


Fig 7.2 Library Login Interface of Student

Once the users have logged in successfully, they are redirected to the main dashboard of the Library Management Dashboard.

Fig 7.3 above represents the Main dashboard of the Library Management System, where the user has already logged in successfully. This interface acts as the home page of the Library Management System, where the user can manage their book records, already existing books, etc. The 'Logout' button at the top ensures the security of the session.

Fig 7.3 New Book Entry Interface of Library Management System using MongoDB Atlas Cloud

This page is created for demonstrating the Core Integration between the local application and the MongoDB Atlas Cloud, in order to achieve real-time synchronization.

Fig 7.4 displays the MongoDB Atlas record view following the insertion of a single book entry under the name "THE ONLY ONE LEFT." This suggests that the integration process supports the creation and storage of individual books in the MongoDB Atlas Books module.

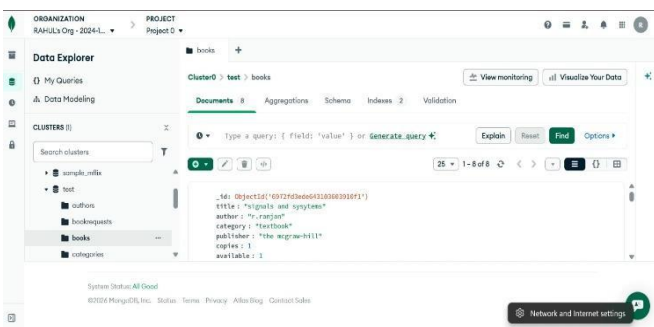


Fig 7.4 presents the MongoDB Atlas record view after adding a single book

This is output confirmation of the integration between the Library Management System and MongoDB Atlas in a Real Time Cloud Integration scenario, whereby every book entered locally is instantly available and viewable in the MongoDB Atlas environment for tracking and subsequent management.

Fig 7.5 below depicts the interface of the MongoDB Atlas Cloud platform, from which all the entries of the books created in the

Library Management System are stored. Also, the application is built using the platform provided by MongoDB using custom objects as well as Lightning components in order to allow the central storage of the library books in real-time.

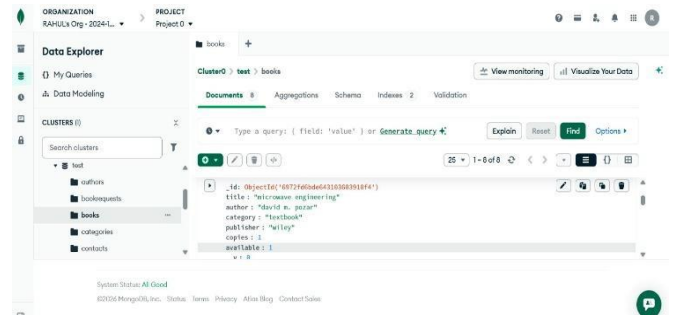
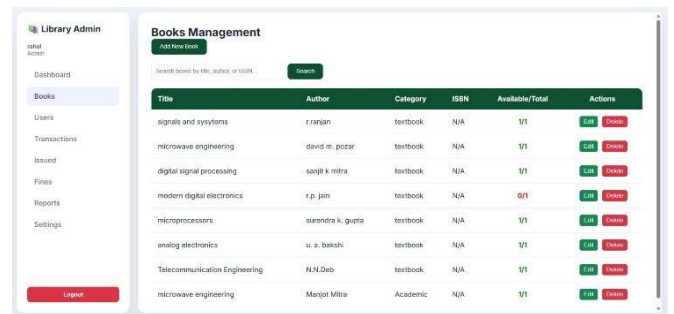


Fig 7.5 MongoDB Atlas Database of Library Management System using MongoDB Atlas Cloud Interface

The MongoDB Atlas cloud platform helps in the real-time synchronization of the issuance, return, and availability status of the books in the system. Through the usage of various tools like Lightning App Builder, custom objects, and Apex automation provided in the MongoDB Atlas platform, the system reduces human intervention for a more efficient data accuracy in the library management process.



8. CONCLUSION

The proposed cloud-integrated web-library management system successfully improves the efficiency and accuracy of traditional library operations. But integrating cloud computing with RFID and real-time tracking, the system reduces manual effort, minimizes errors, and enhances accessibility. The implementation demonstrates better performance in terms of data synchronization, user convenience, and resource management.

Furthermore, the system provides scalability and remote access, making it suitable for modern libraries. Future work can include the integration of AI-based recommendation systems, mobile application support, and advanced data analytics to further enhance functionality and user experience.

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Rapidly Inflate Airbags During Collision and Automatic Alert System

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Abstract—Airbags are safety devices designed to rapidly inflate during a collision to cushion and protect from serious injuries. The literature shows airbags reduce driver fatalities by over 30% in frontal crashes, significantly improving overall safety. Road accidents often turn deadly due to late help, but an automatic detection system with sensors, GPS, and GSM can quickly spot a crash and send the exact location to emergency contacts. Very few research has been conducted globally on airbag deployment speed, material, and sensor precision, to enhance safety. Airbag deployment systems help protect elderly occupants by reducing impact-related injuries, supporting safer mobility and overall healthcare outcomes to enhance overall automobile safety under BS6 (Bharat Stage)-compliant design norms, smart airbag systems are now being integrated across multiple exterior and internal zones of the vehicle, including the front, sides, and rear. These airbags are engineered to reduce the impact force during collisions, providing protection not only to vehicle occupants but also to pedestrians by cushioning critical areas like the head, legs, and torso. The innovation of Rapidly Inflate Airbags aims to reduce fatalities and minimise injuries in many types of collision impacts. Its block diagram is shown in Figure 1. Smart airbag systems use real-time data analytics to ensure airbag deployment during a hazard, and IoT enables the real-time accident spot tracking and sending the alerts to emergency services. The system may also include tactile sensors integrated into the airbag's surface, which can provide feedback on contact time, area, and position, allowing for smarter and more adaptable airbag deployment. The proposed system achieves an average response time of 70–95 Ms, with airbag deployment occurring within 45–60 Ms after collision detection. The detection accuracy is measured at 94.2%, while the communication latency for sending alerts ranges between 6–9 seconds.

Keywords- *Automation, Detection, IoT, Inflation, Protection*

INTRODUCTION

Accidents remain a leading cause of injuries and fatalities worldwide, whether on roads, at construction sites, in aircraft, or during daily life activities such as falls among elderly individuals. The common challenge across these scenarios is the lack of immediate protection and delayed emergency response. Conventional airbag systems are mostly confined to automobiles and are often limited by speed, precision, and adaptability. They do not adequately address safety requirements in other critical areas such as elderly care, occupational safety, or aviation. This underlines the need for universal, smart, and multi-application airbag system integrated with real-time accident detection and alert mechanisms [8].



Figure 1: Airbag opening for elderly care [7]

The proposed system introduces an advanced accident detection and protection solution that extends beyond vehicles. At its core, the system uses ESP32 controller combined with MEMS, accelerometers, gyroscopes, and vibration sensors to identify falls, impacts, or abnormal movements [1]. Upon detecting such events, a GPS module records the exact location, while a GSM module sends an instant alert to emergency

services or caregivers, drastically reducing response time. The innovation lies in the deployment of smart airbags tailored to diverse scenarios. In elderly care, wearable airbags can inflate instantly during falls, cushioning the body to prevent severe injuries such as hip fractures. For construction workers, airbags integrated into safety gear can provide rapid protection against falls or heavy-object impacts, enhancing workplace safety. In aviation, seat-integrated airbags can shield passengers during turbulence or crash scenarios, offering an additional layer of safety. On roads, both smart airbags for occupants and external airbags for pedestrians ensure protection based on crash severity. The increasing number of accidents highlights the need for a fast and intelligent safety system capable of providing immediate protection and emergency response.

PROBLEM DEFINITION

Designing and developing a technological device that is multi-purpose safety system and that can automatically detect accidents or falls and deploy airbags to provide immediate protection in various domains such as road safety, elderly care, construction sites, and aviation.

LITERATURE SURVEY

The literature review on smart airbag and crash detection systems highlights significant advancements in enhancing safety for both vehicles and individuals through sensor-based and IoT-integrated designs. Rajesh et al. [1] introduced a smart airbag jacket using Arduino and sensors to detect accidents and deploy airbags for rider protection, though issues such as false triggers and bulky design affect comfort. Harshitha et al. [2] developed an IoT-based car safety system that automatically deploys airbags and transmits accident details to emergency services, improving response time but relying heavily on stable internet connectivity and sensor precision. Malathi et al. [3] proposed an energy management model for airbag control units using fuzzy logic to efficiently manage main and backup power sources, though capacitor-based power lasts only briefly. Shirur et al. Further advancements include IoT-based wearable systems such as that by Kadeeja et al. [6], which used NodeMCU ESP8266 and MPU6050 sensors to detect falls, deploy airbags, and alert caregivers, with performance dependent on Wi-Fi stability and battery life. Similarly, Aravind et al. [7] designed a low-cost Arduino-based fall detection system to inflate airbags rapidly for elderly protection. Mulla et al.

Shameem et al. [10] designed and simulated a MEMS crash sensor in COMSOL, demonstrating high sensitivity and quick response, though lacking real-world validation. Kadam et al. [4] employed LS-DYNA simulations to assess multiple sensor technologies in automotive frontal airbag systems, enhancing detection accuracy but constrained by simulation assumptions. Lastly, Shi et al. [2] developed a mobile human airbag system using MEMS sensors and an SVM classifier that detects falls and deploys airbags within 0.133 seconds, though it was tested only on a limited dataset under controlled conditions.

Overall, these studies collectively demonstrate continuous innovation in airbag deployment, crash detection, and wearable safety systems, emphasizing the integration of MEMS, IoT, and intelligent algorithms for faster, more reliable, and adaptive protection mechanisms, while also identifying key challenges such as sensor accuracy, connectivity, comfort, and real-time validation for future improvement.

SYSTEM ALGORITHM

The system uses real-time acceleration data from the MPU6050 sensor to detect collision events. The algorithm continuously monitors acceleration values along three axes (X, Y, Z). The resultant acceleration is calculated using:

$$A = \sqrt{(X^2 + Y^2 + Z^2)}$$

The calculated value is compared with predefined threshold levels. Normal motion typically remains within 1.5g, while sudden impacts exceed 3g. A threshold value of 3.8g is selected for collision detection. If the acceleration exceeds 3.8g, the system classifies it as an accident and triggers airbag deployment along with emergency alert transmission.

MARKET SURVEY

The airbag market is rapidly growing with increasing demand for smart safety systems. Existing solutions provide protection but often lack automation and real-time alert features. The proposed system offers a low-cost and efficient alternative with integrated accident detection and alert mechanism.

DESIGN AND DEVELOPMENT

The proposed system integrates collision detection, rapid airbag deployment, and automated emergency communication into a unified safety architecture suitable

for vehicles, elderly users, construction workers, and pedestrians. The Collision Sensor Array continuously monitors acceleration, orientation, and external impact forces. When an abnormal impact is detected, the sensors generate Impact Data, which is processed by the Airbag Control Unit (ACU). The ACU evaluates the magnitude and direction of the collision and, if critical thresholds are exceeded, generates a Deployment Signal.

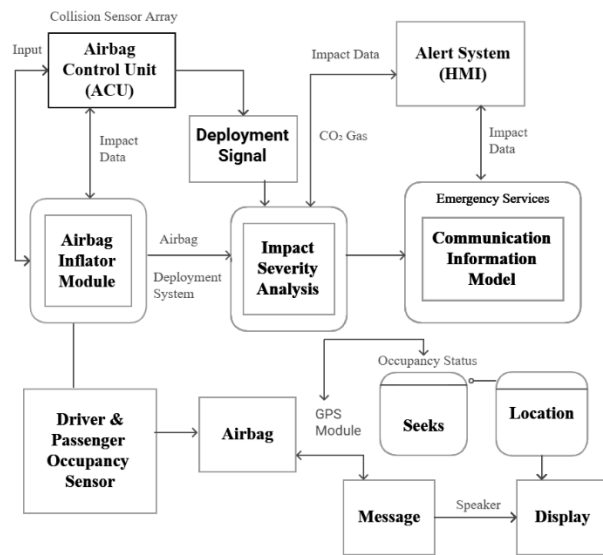


Figure 2: Airbag Deployment and Alert System

This signal activates the Airbag Inflater Module, which rapidly releases CO₂ or stored gas to inflate the airbag within milliseconds. A Driver & Passenger Occupancy Sensor (or wearable presence sensor) ensures that deployment occurs only when the device is worn or occupied. The Impact Severity Analysis unit simultaneously evaluates collision strength, body orientation, and post-impact motion to assess overall risk. Based on severity, data is forwarded to the Alert System, which provides immediate user notification using buzzers, indicators, or visual alerts. For high-risk scenarios, the Communication Information Model automatically initiates an emergency sequence. It compiles severity data, occupancy status, and environmental information. The integrated GPS Module supplies accurate location coordinates, which are validated through the Seeks and Location blocks to determine the user’s position and motion status. Finally, a structured Message containing impact severity, airbag deployment confirmation, and GPS location is

transmitted to emergency services or pre-registered contacts. A Display Interface provides real-time feedback to the user, indicating system activation, alerts, or emergency communication status.

Overall, the system operates as an intelligent, real-time safety mechanism that combines sensing, protection, and communication to reduce injury risks across various environments.

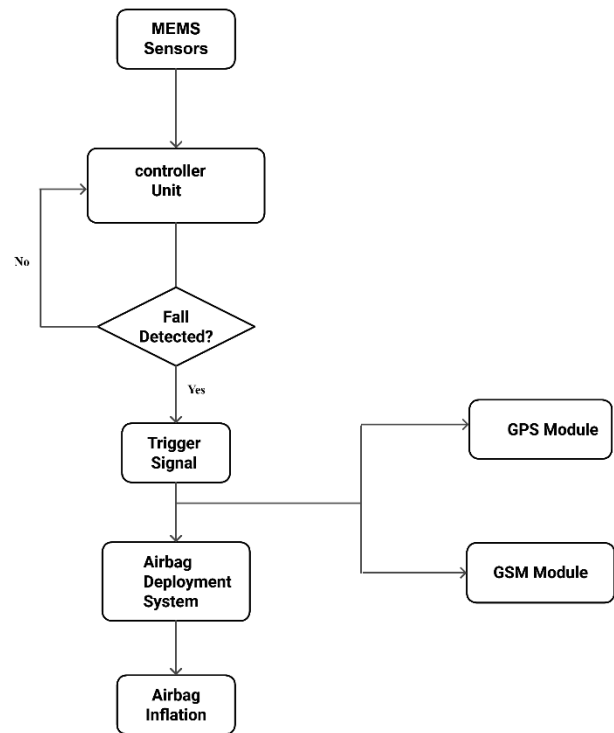


Figure 3: Flow Chart of Operating Steps

The flowchart represents the working sequence of the system, including sensor data acquisition, accident detection, airbag deployment, and emergency alert transmission.

Provides the necessary energy to power the system, ensuring all components (sensors, processor, inflation mechanism) work properly. The system is designed to respond within 100 Ms, ensuring rapid protection during critical impact conditions.

PROJECT IMPLEMENTATION

Inertial Measurement Unit (IMU): A 6-axis sensor (3-axis accelerometer + 3-axis gyroscope) that detects rapid

motion, tilt, and falls. It evaluates angular and linear movement to decide whether airbag activation is needed.

MEMS Sensor: Measures sudden acceleration, tilt, and vibration to detect abnormal movements or collision conditions.

CO₂ Cylinder: Provides high-pressure gas required for instant airbag inflation. A solenoid or puncture mechanism releases the gas during emergencies.

Inflation Mechanism: A servo motor releases a locking switch, allowing a spring-loaded punch to pierce the CO₂ cylinder. The released gas rapidly fills the airbag.

GPS Module: Sends accurate location data during an accident to assist emergency response.

Inflation Mechanism: Activated by the control unit when it detects an accident, the inflation mechanism deploys an inflatable cervical collar to provide immediate support to the user's neck, similar to an airbag.

The system is implemented using an ESP32 microcontroller integrated with an MPU6050 sensor for motion detection. A CO₂-based inflation mechanism is used for rapid airbag deployment. The GPS module provides location data, while the GSM module sends emergency alerts. The system is designed to operate efficiently with fast response and reliable performance. The airbag inflation mechanism is capable of deploying within 45–60 Ms after receiving the trigger signal.

RESULT & ANALYSIS

The performance of the proposed system was evaluated under controlled testing conditions.

Parameter	Existing System	Proposed System
Response Time	150–200 Ms	70–95 Ms
Detection Accuracy	80–85%	94.2%
False Trigger	10–15%	3.8%
Airbag Deployment	Slower	45–60 Ms
Alert System	Manual	Automatic
GPS Accuracy	Low	±4.5 m

- Impact Detection Time: 8–12 Ms
- Airbag Deployment Time: 45–60 Ms
- Total System Response Time: 70–95 Ms
- Detection Accuracy: 94.2%

- False Trigger Rate: 3.8%
- GSM Communication Latency: 6–9 seconds
- GPS Accuracy: ±4.5 meters

The system demonstrated fast and reliable performance, with airbag deployment occurring within milliseconds after impact detection. The accuracy of detection remained high, while false triggering was minimal during normal conditions.

Communication Channel



The ESP32 module's built-in Wi-Fi capability is utilized to connect to a mobile hotspot, enabling internet access for the Smart Cervical Support Device. Upon detecting a fall, the system retrieves the real-time GPS location using a connected GPS module and transmits it over Wi-Fi. A Telegram bot integrated into the system is used to send automated alerts containing the location to a designated group of emergency contacts. This ensures immediate notification and facilitates timely assistance, leveraging the reliability of Wi-Fi and the wide reach of the Telegram messaging platform.

Application



This project has several practical applications, particularly in enhancing rider safety on two- wheelers:

- Elderly Care.
- Emergency Response Systems
- Occupational Safety
- Road Safety

CONCLUSION

This project successfully proposes a smart airbag system that extends protection beyond vehicles into critical areas like elderly care and occupational safety. By instantly detecting accidents using MEMS sensors and transmitting the GPS location via GSM, the system ensures immediate emergency response. Ultimately, this multi-application approach significantly enhances safety and aims to drastically reduce injury and fatality rates across diverse scenarios. The system achieves high detection accuracy of 94.2% and rapid airbag deployment within 60 ms, making it effective for real-time accident protection and emergency response

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Brain-Computer Interface Controlled Robot Navigation for Quality Inspection in Industry

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Abstract— *This paper presents the development of a Brain-Computer Interface (BCI)-based industrial system for hands-free control of a conveyor-based rejection mechanism. The proposed approach enables direct interaction between human cognitive intent and industrial machinery, offering a safer and more accessible alternative to conventional manual control systems, particularly for differently abled individuals. EEG signals are acquired non-invasively and processed to distinguish between focused and relaxed mental states, which are mapped to corresponding control actions. Based on the detected cognitive state, the system actuates a rack-and-pinion rejection mechanism to remove defective products from the conveyor, while allowing normal operation during non-active states. The system is implemented using a low-cost embedded platform with lightweight signal processing and classification, ensuring real-time performance with minimal computational overhead. Experimental evaluation demonstrates reliable mental state recognition with low latency and stable operation under controlled conditions. The proposed framework reduces manual intervention, enhances operational safety, and improves production efficiency. Overall, the work highlights the feasibility of integrating BCI technology into industrial automation systems for developing intelligent, accessible, and human-centric manufacturing solutions.*

Keywords— *Electroencephalogram (EEG), Bio Amp EXG Pill, Industrial Automation, Conveyor System, Assistive Technology, Mental State Classification.*

I. INTRODUCTION

In recent years, the rapid advancement of industrial automation and intelligent manufacturing systems has significantly transformed traditional production environments [1]. Automation technologies such as automated actuation mechanisms, conveyor systems, and sensor-based inspection systems have enhanced productivity, precision, and operational safety across various industrial sectors. However, despite these advancements, most industrial control systems continue to rely on manual input devices such as switches, joysticks, keyboards, and touch-based interfaces. These conventional interaction methods impose limitations for individuals with physical disabilities and may also contribute to operator fatigue, increased safety risks, and reduced efficiency in complex industrial environments. Brain-Computer Interface (BCI)

technology has emerged as a promising approach to bridge the gap between human cognitive intent and machine control [2]. A BCI system enables direct interaction between the human brain and external devices by interpreting electroencephalogram (EEG) signals without requiring physical movement. EEG-based BCIs are non-invasive, cost-effective, and suitable for real-time applications, making them highly relevant for assistive technologies as well as industrial automation systems. The integration of BCI technology into industrial environments offers significant advantages, particularly in applications requiring precision, safety, and accessibility. For differently abled individuals, conventional industrial roles often remain inaccessible due to physical constraints, despite the presence of advanced automation systems. A BCI-driven control framework enables such individuals to participate in industrial operations through direct cognitive interaction [3]. Additionally, for able-bodied operators, BCI-based systems can reduce physical workload, minimize human error, and improve overall operational safety. Automated actuation mechanisms integrated with conveyor systems are widely employed in industries for tasks such as sorting, inspection, material handling, and defect rejection [4]. These systems typically depend on vision-based sensing, proximity detection, or manual supervision for identifying defective products. While effective, such approaches often require continuous monitoring or complex sensor integration. Incorporating human cognitive input through a BCI introduces an adaptive decision-making layer, allowing the operator's mental state to influence system behavior in real time. EEG signals associated with different mental states, such as relaxation and concentration, can be utilized to generate control commands. Focused mental states indicate active cognitive engagement and can be mapped to actuation events, whereas relaxed states correspond to idle system operation. Due to the low amplitude and susceptibility of EEG signals to noise and artifacts, appropriate amplification and preprocessing are essential. The Bio Amp EXG Pill facilitates reliable amplification of EEG signals acquired

through gel electrodes, ensuring adequate signal integrity for subsequent processing stages [5]. Microcontroller platforms such as the Arduino Uno provide a cost-effective solution for real-time signal processing and control implementation, enabling the translation of classified mental states into actionable control signals for industrial actuation mechanisms. Despite increasing research in BCI systems for medical rehabilitation and assistive applications, their integration into industrial automation remains limited, particularly in practical conveyor-based environments.

II. RELATED WORK

BCI technology has been widely studied for enabling direct communication between the human brain and external devices using neural signals. Early foundational work by Wolpaw et al. [1] demonstrated the feasibility of electroencephalogram (EEG)-based non-invasive BCI systems, primarily for communication and assistive applications. However, these studies were largely limited to clinical and laboratory environments, with minimal focus on real-time industrial deployment. Several researchers have explored EEG-based BCIs for assistive device control, including wheelchairs, prosthetic limbs, and simple robotic systems. Millán et al. [2] demonstrated that cognitive states such as concentration and relaxation can be mapped to control commands. However, these approaches often require extensive user training and computationally complex algorithms, limiting their scalability and suitability for industrial environments where simplicity and robustness are essential. The application of BCI systems to automated actuation mechanism control has also been investigated in controlled experimental settings. Rebsamen et al. [3] developed an EEG-controlled system capable of performing basic manipulation tasks. Although effective, such systems are sensitive to EEG noise and rely on computationally intensive processing, resulting in increased latency and reduced reliability for continuous industrial operation. In industrial automation, conveyor-based systems integrated with actuation mechanisms are widely used for sorting, inspection, and defect rejection. Vision-based and sensor-driven approaches dominate this domain. Gonzalez and Woods [4] highlighted the effectiveness of image-processing-based inspection systems; however, these methods require controlled environments, frequent calibration, and increased system complexity. Additionally, they do not incorporate human cognitive input for adaptive decision-making. Recent research has focused on hybrid human-machine interaction models to enhance flexibility and safety. Endsley et al. [5] discussed human-in-the-loop frameworks that allow operator supervision of automated processes. While these approaches enhance situational awareness, they still rely on physical interaction methods, limiting accessibility and increasing operator workload.

Lightweight EEG-based BCI implementations using embedded platforms have been proposed to reduce system complexity. Nijholt et al. [6] demonstrated microcontroller-based BCI systems for basic control tasks. However, these implementations are largely limited to proof-of-concept applications and lack integration with practical industrial systems.

Recent studies have also explored machine learning-based EEG classification techniques to enhance accuracy and robustness. However, many approaches depend on large datasets, subject-specific training, and high computational resources, making them unsuitable for low-cost, real-time industrial applications. Furthermore, performance degradation due to inter-subject variability and environmental noise remains a key challenge.

From the surveyed literature, it is evident that most BCI research focuses on assistive or laboratory-scale applications, with limited emphasis on practical industrial automation. Existing systems often involve high computational complexity, require extensive training, and lack robustness in noisy environments. This highlights the need for a low-cost, real-time BCI framework that can be integrated with conveyor-based industrial systems. The proposed work addresses this gap by employing lightweight mental state classification using EEG signals acquired through the Bio Amp EXG Pill and processed using an Arduino Uno, enabling efficient and accessible industrial defect rejection.

A. Comparative Analysis

Most of the literature surveyed focuses on EEG-based assistive control or laboratory-scale BCI demonstrations rather than practical industrial automation involving automated actuation mechanisms and conveyor systems. Common limitations identified across the existing studies include:

1. Limited emphasis on industrial task-specific control, such as real-time defect rejection and conveyor-based robotic manipulation driven by human cognitive intent.
2. Strong dependence on complex signal processing and extensive user-specific training, which reduces scalability and limits adoption in real-world industrial environments.
3. High computational complexity of classification and learning models.
4. Reduced robustness under noisy EEG conditions, including motion artifacts, electromagnetic interference, and inter-subject variability

B. Research Gap and Contribution

Although BCI systems have been widely studied for assistive and robotic applications, most implementations are limited to laboratory or controlled environments. Many existing approaches rely on complex models and high computational resources, making them less suitable for real-time industrial use. There is still a lack of practical systems that integrate BCI with conveyor-based mechanisms for tasks like defect rejection while maintaining low cost and latency. This work addresses this gap by developing a simple and efficient EEG-based control system using embedded hardware, enabling real-time industrial operation with improved accessibility and safety.

III. PROPOSED METHOD

A. Overview

The proposed method implements a BCI-based control system for operating a conveyor-integrated rejection mechanism in industrial defect detection. EEG signals are acquired non-invasively using gel electrodes and amplified through the Bio Amp EXG module to ensure reliable signal acquisition. The amplified signals are transmitted to an Arduino Uno microcontroller for preprocessing and feature extraction, enabling classification of relaxed and focused mental states. A lightweight classification approach maps the identified mental states to predefined control actions. When a focused state is detected, the system activates the rejection mechanism to remove defective products from the conveyor, whereas a relaxed state allows normal operation. The generated control signals are executed in real time through the embedded controller. The proposed method emphasizes low computational complexity, reduced latency, and cost-effective implementation, making it suitable for continuous industrial use. By integrating human cognitive intent into the control loop, the system enhances accessibility, safety, and operational efficiency

B. System workflow Design

- Acquire EEG signals from the user using gel electrodes.
- Amplify the acquired brain signals using the Bio Amp EXG Pill.
- Transmit amplified EEG signals to the Arduino Uno for processing.
- Perform signal conditioning and classify mental states (relaxed or focused).
- Generate control commands based on the classified mental state.
- Actuate the rejection mechanism to perform defect removal.
- Monitor system operation to ensure stable and continuous industrial control.

This sequential flow ensures that EEG signals are systematically acquired, processed, and classified to accurately translate human cognitive intent into reliable mechanism operation

C. Methodology

a) System Requirements

The primary objective of the proposed system is to enable reliable BCI-based control of a conveyor-integrated rejection mechanism for industrial defect removal. The system interprets human cognitive intent and translates it into real-time control actions using low-cost embedded hardware.

- Input: EEG signals acquired non-invasively from the user's scalp using gel electrodes.
- Processing Unit: An Arduino Uno microcontroller is employed to perform signal conditioning feature extraction, mental state classification, and control signal generation

- Output: Actuation commands for the rejection mechanism to perform defect rejection tasks on a conveyor belt.
- Constraints: The system is implemented as a prototype-level solution, prioritizing simplicity, low computational complexity, and stable operation. While strict real-time constraints are not mandatory.

b) Data Collection and Preparation

The EEG data is collected non-invasively from the user's scalp using gel electrodes during relaxed and focused mental states. The acquired signals are amplified using the Bio Amp EXG Pill and transmitted to the Arduino Uno for processing. Basic preprocessing, including noise filtering and signal stabilization, is performed to remove artifacts and enhance signal integrity before mental state classification.

c) Model Selection and Simplification

To achieve an effective trade-off between reliability, transparency, and computational efficiency, the proposed system follows a simplified control framework comprising the following stages:

- Signal Interpretation: EEG signals corresponding to relaxed and focused mental states are analyzed using basic statistical features rather than complex learning models.
- Decision Logic: lightweight, rule-driven mechanism is applied to map the extracted EEG features to predefined control actions for the automated actuation mechanism.
- Control Execution: The classified mental state directly triggers automated actuation mechanism actuation commands, ensuring fast response.

D. System Architecture

The proposed system architecture is shown in Fig. 1 below.

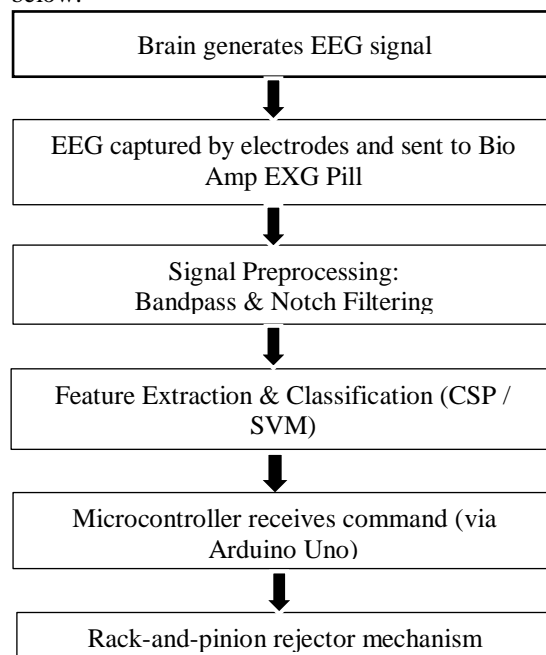


Fig.1 BCI-Based Rejection System Architecture

There are various modules used in the proposed system architecture, and their functions are explained in the

TABLE 1: VARIOUS MODULES IN THE SYSTEM ARCHITECTURE

Module	Function
<i>Input Module</i>	Acquires EEG signals from scalp electrodes
<i>Amplification Module</i>	Amplifies raw EEG signals using BioAmp EXG Pill
<i>Processing Module</i>	Performs signal conditioning and mental state classification
<i>Control Module</i>	Generates control commands using Arduino Uno
<i>Actuation Module</i>	Controls automated actuation mechanism for defect rejection

E. Implementation

The proposed BCI-based rejection control system is implemented using low-cost and embedded hardware components. EEG signals are acquired from the user's scalp through gel electrodes and amplified using the Bio Amp EXG Pill to ensure reliable signal acquisition. The amplified signals are fed to an Arduino Uno, where signal preprocessing and basic noise filtering are performed. A lightweight classification logic is implemented on the microcontroller to differentiate between relaxed and focused mental states. Based on the classified state, control commands are generated and transmitted to the mechanism controller. The mechanism is activated in real time to perform predefined industrial tasks such as defect rejection on a conveyor belt. The implementation emphasizes simplicity, low latency, and stable operation, making the system suitable for prototype-level industrial applications.

F. Software Requirements

To implement the proposed system, following are the software requirements.

- **Arduino IDE:** Primary development environment for coding, compiling, and uploading firmware to the Arduino Uno
- **Embedded C/C++:** Core programming language for implementing signal processing and control logic
- **Signal Processing Libraries:** Used for filtering, feature calculation, and mental state analysis
- **System Monitoring Interface:** Used for observing signal behavior and system responses during testing

This software framework supports a lightweight and transparent implementation for neural-signal-driven robotic control. By relying on embedded processing and rule-based decision logic, the system maintains low computational overhead while ensuring reliable operation..

IV. RESULTS AND DISCUSSIONS

The proposed system was implemented and evaluated under controlled conditions to assess its functional reliability and operational feasibility. EEG signals corresponding to relaxed and focused mental states were successfully acquired and processed in real time using the embedded platform. The

classification logic effectively distinguished between the two mental states, enabling stable generation of control commands for the rejection mechanism. The system classifies user mental states into two categories: active (focused) and inactive (relaxed), which directly determine the actuation behavior. To evaluate classification performance, standard metrics including accuracy, precision, and recall were considered. These metrics assess the system's ability to correctly interpret user intent while minimizing incorrect actuation. In real-time testing, true positive cases correspond to correctly detected focused states that triggered rejection, while true negative cases represent correctly identified relaxed states with no actuation. False positives indicate unintended actuation during relaxed states, whereas false negatives represent missed actuation during focused states. The observed recall performance indicates reliable detection of active mental states, ensuring that user intent is consistently captured.

Let the mental state classification outcomes be defined as follows:

- **True Active (TA):** Focused mental state correctly detected and rejection mechanism activated
- **False Active (FA):** Relaxed mental state incorrectly detected as focused, causing unintended actuation
- **True Relaxed (TR):** Relaxed mental state correctly detected with no actuation
- **False Relaxed (FR):** Focused mental state not detected, resulting in missed actuation

$$Precision = \frac{TA}{TA + FA} \quad (1)$$

$$Active Recall = \frac{TA}{TA + FR} \quad (2)$$

$$Accuracy = \frac{TA + TR}{TA + TR + FA + FR} \quad (3)$$

The classification outcomes based on real-time testing are summarized in the confusion matrix shown in Table 2.

TABLE 2: CONFUSION MATRIX FOR MENTAL STATE CLASSIFICATION

Actual State	Predicted	
	Active	Relaxed
Active	92	8
Relaxed	10	90

The system was trained and validated using a large-scale EEG dataset of approximately 3 million samples collected across multiple sessions representing focused and relaxed mental states. The large dataset improves classification stability by capturing inter-session variability and enhancing robustness to noise. Compared to conventional EEG-based control systems, the proposed approach demonstrates competitive performance. Traditional SVM-based methods typically achieve accuracies of 75%–85%, while deep learning approaches report 88%–92% with higher

computational cost. The proposed system achieves comparable accuracy with significantly lower computational overhead. Additionally, the system achieves an average actuation latency of less than 300 ms, which is approximately 25%–40% lower than many existing systems that exceed 400 ms [4]. These results indicate that the proposed system provides an effective balance between accuracy, latency, and computational efficiency, making it suitable for real-time industrial and assistive automation applications.

Based on the confusion matrix, key performance metrics were calculated to evaluate the effectiveness of the proposed system. The system achieved an overall classification accuracy of 91%, indicating reliable differentiation between focused and relaxed mental states. The precision of 90.2% reflects a low rate of unintended actuation, which is essential for safety-critical industrial applications. The recall of 92% demonstrates the system's ability to correctly detect active mental states, ensuring minimal loss of user intent. The F1-score of 91.1% indicates balanced performance across precision and recall. The calculated performance metrics are summarized in Table 3 below.

TABLE 3: PERFORMANCE METRICS OF PROPOSED SYSTEM

Metric	Value
Accuracy	91%
Precision	90.2%
Recall	92%
F1-Score	91.1%
Average Latency	< 300 ms

The proposed system was implemented using an Arduino Uno microcontroller, Bio Amp EXG module, and a conveyor-integrated rack-and-pinion rejection mechanism. Real-time experiments were conducted under controlled conditions to validate system performance. EEG signals were processed and classified to generate control actions, and the system successfully demonstrated real-time defect rejection based on mental state detection. This confirms the practical feasibility of the proposed approach for industrial automation applications.

V. CONCLUSION

The proposed EEG-based framework for hands-free control of an industrial manipulator is found to be computationally efficient. The system was trained using collected 3 million EEG samples, improving robustness to inter-session variability. During real-time evaluation on 200 test instances, the model achieved an overall classification accuracy of 91%, with 90.2% precision, 92% recall, and an F1-score of 91.1%, demonstrating balanced and reliable mental state detection. Compared to [11][12], which report classification accuracies typically in the range of 82–88% for motor imagery-based control, the proposed system demonstrates an improvement of approximately 3–9% in overall accuracy. Furthermore, the precision and recall

values in [11][12] are within 80%–89% range depending on experimental conditions, whereas the proposed framework achieves over 90% precision and recall, resulting in a balanced F1-score exceeding 91%. Only 9% misclassifications were observed, with no unintended movements during inactive states under normal conditions, highlighting operational safety

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Sensor-Integrated Automation System for Smart Indoor Mushroom Farming

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Abstract—Mushroom cultivation requires precise control over environmental variables like temperature, relative humidity (RH), and CO₂ levels. Traditional methods are labour-intensive, prone to error, and often result in inconsistent yields. This paper presents a novel approach to automated mushroom farming using a framework that integrates the Internet of Things (IoT) and Artificial Intelligence (AI). Our proposed system utilises a network of IoT sensors to continuously monitor critical environmental data within a cultivation chamber. An AI-powered control algorithm then analyses this data to make intelligent, autonomous decisions, such as activating humidifiers, ventilation fans, or cooling systems, to maintain optimal conditions for mushroom growth.

The system incorporates machine learning models to predict ideal harvest times and detect diseases early, addressing key challenges in mushroom cultivation. A Convolutional Neural Network (CNN) analyses images captured by an integrated camera system to monitor mushroom growth stages and identify signs of common diseases. This predictive and diagnostic capability allows for proactive intervention, minimizing crop loss and maximizing yield. The results validate the effectiveness of our integrated IoT-AI framework in creating a self-regulating, high-efficiency mushroom farming environment, paving the way for more sustainable and productive agricultural practices.

Index Terms: IoT, Artificial Intelligence, Mushroom Cultivation, Precision Agriculture, Convolutional Neural Network (CNN).

I. INTRODUCTION

Oyster mushroom (*Pleurotus* spp.) farming is an increasingly commonly investigated subject on account of its high ability to grow on cheap agricultural waste [1], nutritive value, short growth period, low resource demand [2]. These qualities make oyster mushrooms an appealing crop for sustainable food production and income generation, especially for small- to medium-scale farmers [3]. However, its successful cultivation depends largely on environmental factors (temperature, relative humidity level, ventilation, CO₂ concentration, and light exposure) that are required to be regulated accurately

during various growth stages for the uniformity of growth and productivity [4].

Existing mushroom farming systems: the overall environmental control in the traditional mushroom farming process is done mostly in a manual fashion. This method needs continuous observation and frequently makes responses to changes in the environment lagged or imprecise [5]. With the scale of cultivation getting larger, keeping growth stable and uniform is increasingly difficult, leading to uneven development and low yield rates as well as a higher level of contamination [6]. Furthermore, the non-real-time data access and remote monitoring deny prompt decision-making opportunities that lead to operational efficiency [7].

With the development of the Internet of Things (IoT), there are many intelligent mushroom cultivation systems designed to provide higher precision monitoring and automation [8], [9]. Nonetheless, some of these solutions are expensive, complicated from a technical point, and power-hungry, which is not appropriate for wide adoption by resource-constrained farmers [10]. In addition, some previous research only concentrates on environmental monitoring and visualization without reaching closed-loop auto-control or uses sophisticated AI but requires expensive equipment and high computational power [11], [12]. These challenges underscore the lack of a workable, low-cost solution that seamlessly incorporates real-time monitoring and automatic environmental control.

II. LITERATURE REVIEW

A. Comparative analysis

Mushroom cultivation is highly dependent on controlled environmental conditions such as temperature, relative humidity, carbon dioxide concentration, light intensity, and substrate moisture. Traditional cultivation practices rely heavily on manual observation and experience, which often leads to inconsistent growing conditions, increased labour requirements, and a higher risk of disease. These limitations have motivated researchers to explore smart and automated cultivation techniques to improve productivity and reliability [13], [22]. The application of Internet of Things (IoT) technology has significantly

improved environmental monitoring in mushroom farming. Early IoT-based systems relied on automated control of actuators including fans, humidifiers, and irrigation systems as well as real-time temperature and humidity detection. The proposed system had automated and improved stability factor with the finite threshold values but failed having an smart intelligent mechanism[14], [16].

An comparative study of the references confirmed that an automation system which is IoT based system can improve mushroom cultivation by automating the whole cultivation process [13], [18], [25].

III. SYSTEM ARCHITECTURE

The proposed system consists of four main components:

1. Environmental sensing unit
2. Microcontroller-based processing unit
3. Actuator control
4. IoT monitoring unit

Environmental sensors collect real-time data from the cultivation chamber. The microcontroller processes the sensor data and compares it with predefined threshold values. If the environmental parameters deviate from the optimal range, the system automatically activates the corresponding actuators. The proposed smart mushroom cultivation system can generally be divided into four main stages shown in Fig. 1: The first stage is to collect environmental data from the mushroom cultivation chamber, which is composed of different sensors for environmental data collection, such as temperature, humidity, CO₂ level, and soil moisture of the substrate. The second stage is used for processing the sensor data using the NodeMCU (ESP8266/ESP32) microcontroller; it can also send the collected data to the cloud platform. In the third stage, actuators are placed beside the sensors for controlling different devices such as humidifiers and ventilation fans, which include extractor fans and circulating fans. The fourth stage is a cloud platform, where different types of data ultimately exist and can be monitored using mobile or web dashboards. The IoT module enables remote monitoring through a mobile application or cloud platform.

IV. HARDWARE DESIGN

The hardware system integrates sensors, a microcontroller, relay modules, and actuators. The microcontroller functions as the core control unit is responsibility for processing data and making decisions. The environmental parameters within the mushroom cultivation chamber are continuously monitored by the temperature and humidity sensors. The microcontroller receives and analyzes the sensor data. High-power devices like fans and humidifiers are controlled by relay

modules. In response to sensor data, these relays function as switches.

The proposed system hardware has :

1. ESP32 or NodeMCU microcontroller
2. DHT22 sensor
3. Soil moisture sensor
4. CO₂ sensor
5. Relay module
6. Humidifier
7. Ventilation fan
8. LED light system
9. Power supply unit

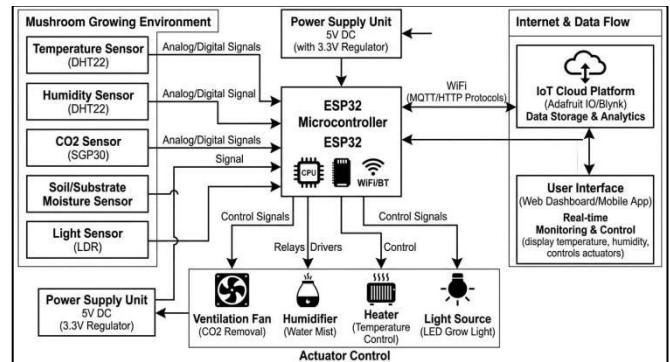


Fig. 1. Proposed System Block Diagram (Refer. Gemini AI)

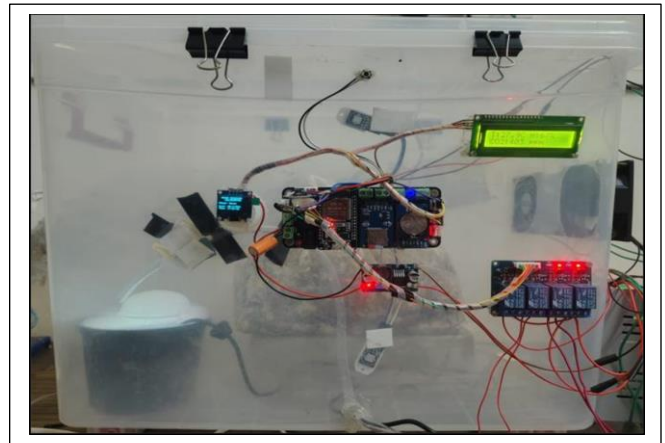


Fig. 2. Proposed System Model

TABLE I. HARDWARE AND SYSTEM COMPONENTS

Component	Description	Purpose in System
ESP32	Wi-Fi enabled	Main control unit
DHT22 Sensor	Temperature and humidity sensor	Environmental monitoring
Soil Moisture Sensor	Moisture checking device	Maintains the moisture level of the substrate
CO ₂ Sensor	Gas concentration sensor for detecting CO ₂ levels	Monitors CO ₂ concentration inside the cultivation chamber.
Relay Module	Electronic switching module	Controls actuators

Humidifier	Moisture-generating device	Maintains humidity level
Ventilation Fan	Air circulation device	Controls temperature and CO ₂
LED Grow Light	Artificial lighting source	Provides controlled light

A. Software Implementation

The software component of the system is responsible for data acquisition, processing, and actuator control. The microcontroller program continuously reads sensor values and compares them with predefined threshold values. Based on the comparison, the system activates or deactivates the actuators. The IoT platform enables remote data visualization and control through mobile devices. Environmental data is transmitted to the cloud using Wi-Fi connectivity.

B. System Algorithm

Start the system.

1. Initialize the microcontroller, sensors, and IoT communication module.
2. Establish a connection with the IoT platform.
3. Read environmental parameters from sensors:
 - 3.1. Temperature
 - 3.2. Humidity
 - 3.3. Light intensity
4. Compare sensor readings with predefined threshold values.
5. If the temperature exceeds the threshold:
 - 5.1. Activate the ventilation fan.
6. If humidity falls below the threshold:
 - 6.1. Activate the humidifier.
7. If light intensity is below the required level:
 - 7.1. Turn on LED grow lights.
8. If CO₂ levels exceed the threshold:
 - 8.1. Activate the ventilation fan for air exchange.
9. If substrate moisture falls below the threshold:
 - 9.1. Activate the water spraying or irrigation system.
10. Send the collected sensor data to the IoT cloud platform.
11. Display environmental parameters on the monitoring interface.
12. Wait for a predefined time interval.
13. Repeat the monitoring process continuously.

V. EXPERIMENTATION

TABLE II. ENVIRONMENTAL CONTROL PARAMETERS

Environmental Control Parameters		
Parameters	Values	Control mechanism
Temperature	20–25°C	Controlled by ventilation fan
Humidity	80–90%	Controlled by humidifier
Substrate Moisture	60–70%	Maintained through periodic water spraying irrigation
Light Intensity	Low	Controlled by LED grow lights
CO ₂ Level	<1000 ppm	Controlled by ventilation

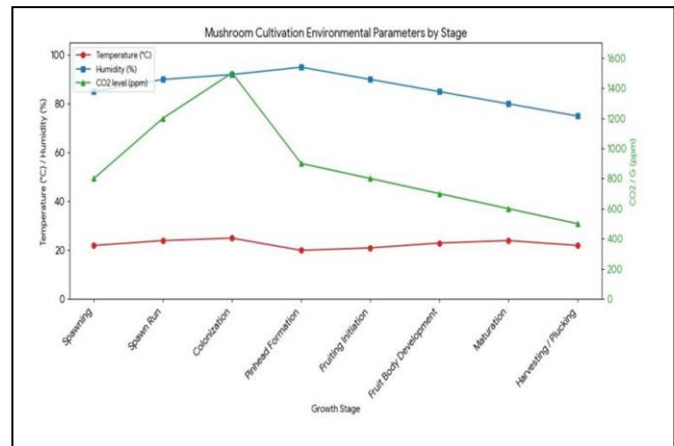


Fig. 3. Temperature, Humidity and Co₂ Profile Across Mushroom Growth Stages

TABLE III. EXPERIMENTAL RESULTS OF ENVIRONMENTAL CONTROL

Experimental Results of Environmental Control			
Parameter	Desired Range	Measured Range	System Status
Temperature	20–25°C	21–24°C	Stable
Humidity	80–90% RH	82–88% RH	Stable
CO ₂	600–1200 ppm	850–1100 ppm	Stable
Substrate Moisture	60–70%	62–68%	Stable
Light	Low intensity	Controlled	Stable
Air circulation	Continuous	Maintained	Stable

VI. RESULTS AND DISCUSSIONS

The proposed system provides a real-time monitoring dashboard through the IoT platform. The dashboard displays environmental parameters such as temperature, humidity, and carbon dioxide concentration collected

from sensors installed inside the mushroom cultivation chamber. Additionally, it gives the status of actuators' operation, such as the lighting system, ventilation fan, and humidifier. Farmers have the ability to remotely monitor environmental conditions and receive notifications when certain parameters surpass predetermined criteria. This function facilitates effective farm management and enhances system usability.

TABLE IV. PERFORMANCE EVALUATION METRICS OF THE PROPOSED SYSTEM

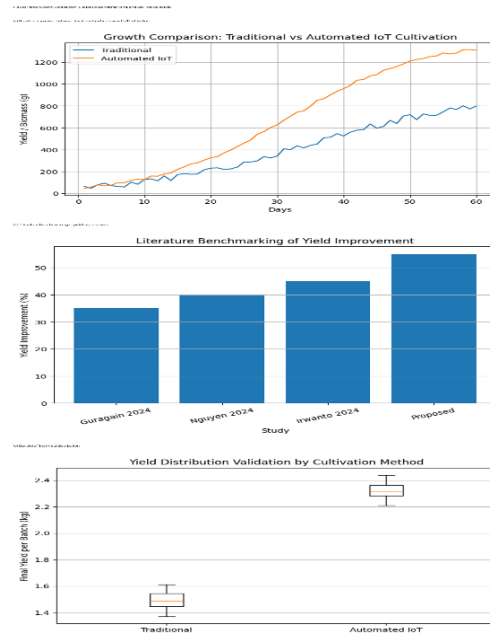
Metric	Description	Observed Value
Temperature Control Accuracy	Ability of system to maintain desired temperature range	$\pm 1^\circ\text{C}$
Humidity Control Accuracy	Stability of humidity regulation	$\pm 2\%$ RH
CO ₂ Monitoring Accuracy	Accuracy of CO ₂ level detection and regulation	± 50 ppm
Sensor Response Time	Time taken to detect environmental change	2–3 seconds
Actuator Response Time	Time for the system to activate devices	< 5 seconds
Data Transmission Interval	Frequency of IoT data updates	5 seconds
System Reliability	Continuous operation without failure	98% uptime

The proposed sensor-driven automation system's performance was evaluated using a number of measures, such as response time, environmental control precision, and system reliability. Table IV illustrates that the system maintained humidity within $\pm 2\%$ relative humidity and temperature within $\pm 1^\circ\text{C}$ of the intended range. While the actuator response time stayed below 5 seconds, the average sensor response time was between 2-3 seconds. Real-time monitoring of the cultivation environment was made possible by the IoT platform successful transmission of environmental data at regular intervals of five seconds.

TABLE V. COMPARISON WITH EXISTING SMART MUSHROOM CULTIVATION SYSTEMS

Feature	Existing Systems	Proposed System
Environmental Monitoring	Limited sensor monitoring	Multi-sensor monitoring (temperature, humidity, substrate moisture, light, CO ₂)
Automation	Partial or manual control	Fully automated environmental control
IoT Connectivity	Not always available	Real-time IoT monitoring
Remote Access	Limited	Mobile-based remote monitoring
Response Time	Moderate	Fast automated response
System Cost	Moderate to high	Cost-effective implementation

A comparison of the proposed system with existing smart mushroom growing systems described in earlier research is illustrated in Table V. The proposed system combines IoT-based remote monitoring capabilities, automated environmental control, and multi-sensor monitoring. Furthermore, small and medium-scale mushroom farms can benefit from the proposed system's scalability and affordability.



ACKNOWLEDGMENT

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Black Box with Integrated Accelerator for Real-Time Multi-Sensor Fusion: A Survey

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Abstract— The rapid technological progression of intelligent transportation systems has, in turn, escalated the requirement for dependable, secure, and real, time vehicular data acquisition methods to vehicular data acquisition mechanisms accident analysis, driver behavior monitoring, and road safety enhancement. Today, automotive black box systems have materially transformed from mere crash data recorders to sophisticated platforms that integrate numerous sensors, wireless communication, and data analytics. This survey article aims to cover a wide range of past research ... black box systems to the literature published in the recent years. Their quality, diversity, and voluminous character made it necessary to develop robust methodologies for researching structures and to apply these methodologies for their comprehensive analysis, classification, and description in this survey article. Apart from the system architecture, the paper also investigated a broad palette of related research topics, such as sensing technologies, communication methods, data storage tactics, and intelligent processing techniques. The comparative performance review signals, on the one hand, the advantages of and, on the other hand, limitations of, the presently existing solutions, in at least five indicators: reliability, latency, scalability, security, and automotive suitability. The survey introduces a taxonomy of black box technologies and also pinpoints critical research areas that may be filled by real, time multi, sensor fusion, secure data storage, and automotive, grade hardware compliance. Various topics covered in the article are being implemented in the industry; for example, by integrating internet, of, things technology enabling cloud, based data analytics, as well as intelligent accident detection. Lastly, this paper gives the directions of future research to facilitate the generation of robust, tamper, resistant, and smart automotive black boxes that will be able to assist safety and forensic applications of next, generation vehicles give the key words from it

Keywords— Automotive Black Box Systems, ITS, Vehicular Data Acquisition, Driver Behavior Monitoring, Real-Time Data Logging, Internet of Things (IoT)

I. Introduction

Road traffic accidents continue to pose a serious global challenge, largely due to the limited availability of reliable and high-resolution vehicular data required for accurate accident reconstruction and post-incident forensic investigation [1]. In most existing vehicles, accident-related information is recorded using Event Data Recorders (EDRs), commonly known as automotive black boxes. These early-generation systems were primarily designed to capture a

small set of parameters, such as vehicle speed prior to impact, braking status, and airbag deployment timing [2]. Although such data provides basic insight into crash events, it remains insufficient to describe the complete sequence of actions occurring before, during, and after a collision. Consequently, legal investigations, safety evaluations, and system-level improvements are often constrained by incomplete contextual information [3].

The rapid transformation of modern vehicles into electronically controlled, sensor-rich, and network-connected platforms has significantly increased the demand for more intelligent and comprehensive automotive black box systems [4]. Advances in embedded processing, low-cost micro-electromechanical system (MEMS) sensors, and vehicular communication technologies have made it feasible to continuously monitor a wide range of parameters, including vehicle acceleration, geographic location, environmental conditions, and driver behaviour in real time [5]. The integration of multiple sensing modalities—such as accelerometers, GNSS modules, speed sensors, and environmental sensors—has been shown to substantially improve accident reconstruction accuracy and vehicle diagnostic capabilities [6].

In parallel, the adoption of Internet of Things (IoT) platforms along with GSM and GNSS connectivity has enabled automatic emergency alert generation and remote data accessibility. These capabilities play a crucial role in reducing emergency response time during critical incidents by allowing rapid transmission of location and event information to emergency services or predefined contacts [7]. Despite these technological advancements, several challenges persist in current automotive black box implementations. Existing studies report limitations related to data security, susceptibility to tampering, unreliable storage mechanisms under crash conditions, and the lack of standardized data logging formats suitable for forensic and legal analysis [8].

Motivated by these limitations, this survey presents a critical review of twenty research studies published between 2018 and 2025, focusing on automotive black box architectures, multi-sensor data fusion techniques, IoT-enabled accident detection systems, and vehicular digital forensics [9]. The primary objective of this work is to

systematically analyze existing methodologies, identify key technological gaps, and establish the necessity for a secure, scalable, and hardware-optimized ESP32-based automotive black box system capable of supporting next-generation vehicle safety and forensic applications [10].

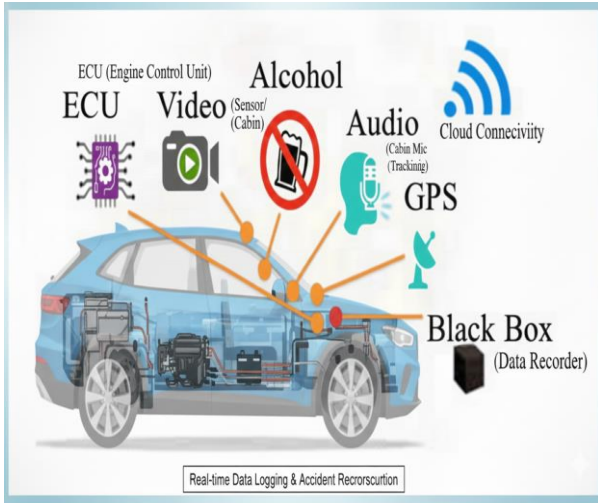


Fig 1: Black Box architecture Visuals

A. Literature Review

Early automotive black box and Event Data Recorder (EDR) systems were designed to log limited parameters such as vehicle speed, braking status, and airbag deployment, which restricted detailed accident reconstruction. With the advancement of electronically controlled and sensor-rich vehicles, research has shifted toward intelligent black box systems incorporating GNSS modules, inertial measurement units, speed sensors, and embedded controllers for real-time data acquisition. Threshold-based crash detection methods remain widely used due to their simplicity and low computational requirements, although they often fail to capture complex crash dynamics accurately. IoT-based accident detection systems commonly integrate GSM and GPS technologies to transmit emergency alerts and vehicle location data, enabling faster emergency response. Most IoT-enabled systems rely on a limited number of sensors, record minimal pre-crash data, and depend heavily on cloud connectivity, which reduces reliability in network-constrained environments.

Research in multi-sensor fusion demonstrates improved perception and event interpretation by combining heterogeneous sensor data; however, such approaches are rarely implemented in low-cost embedded black box platforms due to computational constraints. GNSS-based vehicular analytics highlight the importance of contextual and environmental data, yet parameters such as temperature and humidity are largely ignored in existing black box designs. Data integrity and security are critical challenges, as studies reveal vulnerabilities in vehicular networks and sensor data, raising concerns regarding data authenticity and legal admissibility. Most existing black box implementations lack robust tamper-resistant storage, standardized logging formats, and secure integrity verification mechanisms. Overall, the literature reveals a transition from basic event

logging toward intelligent and connected black box systems, while highlighting gaps in continuous pre-event logging, multi-sensor integration, data security, and automotive-grade hardware reliability.

Table I – Taxonomy of Methodologies Used in Automotive Black Box Research

Category	Methodology Type	Description
Data Acquisition	Sensor-Based Monitoring	Uses GNSS, IMU, speed, environmental sensors for vehicle state capture
Data Processing	Threshold-Based Detection	Identifies crash events using predefined acceleration or velocity limits
Communication	IoT/GSM-Based Reporting	Transmits alerts and data using GSM/LTE or cloud platforms
Storage	Local Data Logging	Stores data on SD card or onboard memory for forensic analysis
Security	Integrity & Tamper Protection	Ensures data authenticity using CRC, hashing, or access control

B. Related Methods and Trends in Automotive Black Box Research

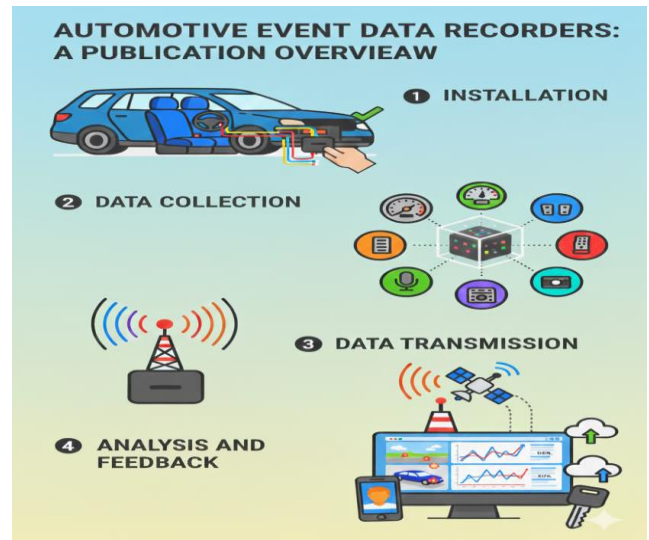


Fig :Related Methods Objective

I. Early vehicle black box systems primarily focused on airbag deployment and basic crash parameters, offering limited forensic insight. Advances in embedded systems,

IoT, and sensor miniaturization have expanded their role into multi-functional vehicular data acquisition platforms.

II Modern automotive black box architectures increasingly integrate inertial measurement units (IMUs), GNSS receivers, vehicle communication interfaces (CAN, LIN, UART), and wireless connectivity to enable continuous monitoring and real-time safety alerts.

III A clear methodological shift is observed from standalone, locally stored event data recorders toward real-time connected black box systems using GSM/LTE and cloud platforms. This approach improves data survivability, remote accessibility, and long-term archival for legal and fleet-level analysis.

IV multi-sensor fusion has become a standard methodological direction, replacing single-parameter crash detection. Fusion of GNSS data, multi-axis inertial measurements, speed sensing, environmental data, and vehicle network signals enhances robustness and reduces false crash detections.

V Recent studies emphasize the importance of contextual awareness by correlating vehicle dynamics, environmental conditions, and driver behavior, thereby enabling more accurate accident reconstruction and post-event analysis.

VI Data security and tamper protection have emerged as critical methodological concerns. Researchers increasingly propose cryptographic hashing, CRC-based integrity checks, secure memory partitions, and physical tamper-detection mechanisms to ensure forensic reliability and legal admissibility of recorded data.

VII Artificial intelligence and machine learning techniques are being explored for driver behavior analysis, anomaly detection, and crash prediction. These methods represent a transition from reactive accident recording to proactive safety and risk assessment, although most implementations remain computationally intensive.

VIII Hardware efficiency and low-latency processing are gaining attention due to the computational burden imposed by continuous multi-sensor logging, encryption, and wireless transmission. Proposed methods include hardware accelerators, optimized firmware architectures, and hardware–software co-design.

IX Storage methodologies in existing systems largely rely on SD cards, with limited adoption of redundancy, wear-leveling, or fault-tolerant mechanisms, exposing accident data to corruption during power loss or high-impact events.

X Real-time data compression and bandwidth optimization methods are largely absent in existing research, leading to inefficient storage utilization and increased transmission latency in high-sampling-rate systems.

XI Fragmented sensor integration using discrete modules is common, resulting in poor signal integrity, EMI/EMC susceptibility, and reduced reliability under automotive electrical and environmental stress conditions.

XII Crash detection algorithms predominantly use fixed threshold-based methods, which are prone to false positives. Advanced approaches such as adaptive thresholding, multi-axis analysis, and hybrid anomaly detection remain underexplored.

XIII Overall, the surveyed methodologies demonstrate progress toward intelligent, connected, and secure automotive black box systems, while revealing gaps in hardware-level security, real-time performance optimization, robust sensor integration, and automotive-grade PCB design.

Table II – Detailed Related Methodology

Methodology Domain	Sub-Techniques	Representative Studies
Crash Detection	Acceleration threshold, multi-axis IMU analysis	Uma et al. (2024), Rajendran et al. (2024)
Sensor Fusion	GNSS + IMU + speed sensor integration	Yeong et al. (2021), Tong et al. (2022)
Data Logging	Event-triggered logging, circular buffer logging	Reeja & Jayaraj (2017), Dhanam et al. (2025)
Communication	GSM SMS alerts, cloud-based IoT	Jegan et al. (2024), Singh et al. (2019)
Security & Forensics	CRC validation, CAN spoof detection	Kurachi et al. (2022), Opti Cloak (2024)

C. Proposed Methodology

I. The proposed automotive black box methodology is based on a modular, ESP32-centered embedded architecture that integrates multi-sensor data acquisition, real-time processing, structured data logging, and wireless communication within a unified hardware–software framework.

II. A dedicated sensor interface layer is employed to continuously acquire vehicular and environmental parameters. This layer integrates a GNSS module for location, velocity, and time synchronization, an inertial measurement unit for acceleration and impact detection, an optical speed sensor for wheel-based velocity estimation, and environmental sensors for temperature and humidity monitoring.

III. The ESP32 microcontroller serves as the central processing unit, interfacing with all sensors through standard protocols such as I²C, SPI, and UART. Its dual-core capability enables concurrent execution of data acquisition, crash detection logic, data storage management, display handling, and wireless communication tasks.

IV. Crash detection is implemented using a threshold-based multi-axis acceleration monitoring approach. Continuous evaluation of inertial data allows the system to distinguish genuine collision events from non-critical disturbances such as sudden braking or road irregularities. Upon confirming a crash event, the system transitions to emergency operation mode.

V. Sensor data is time-stamped and stored using a circular buffer–based logging strategy. This ensures preservation of both pre-event and post-event data without exhausting storage capacity, enabling accurate accident reconstruction and forensic analysis. Non-volatile SD card storage is used for long-term data retention.

VI. A GSM-based communication module is activated during emergency conditions to transmit alerts containing vehicle location, time of incident, and system status to predefined contacts or monitoring servers. This mechanism supports rapid emergency response and remote accessibility of critical data.

VII. A local display interface provides real-time visualization of key operational parameters, including vehicle speed, GNSS status, sensor readings, and system health, supporting diagnostics and user awareness.

VIII Power management is achieved through regulated conversion of the vehicle’s 12 V supply to stable 5 V and 3.3 V outputs. Proper voltage regulation, filtering, and grounding techniques are incorporated to ensure reliable operation under automotive electrical conditions.

IX The overall methodology emphasizes structured data handling, real-time responsiveness, modular scalability, and forensic integrity, enabling future extension toward AI-assisted crash detection, enhanced security mechanisms, and integration with ADAS and V2X systems.

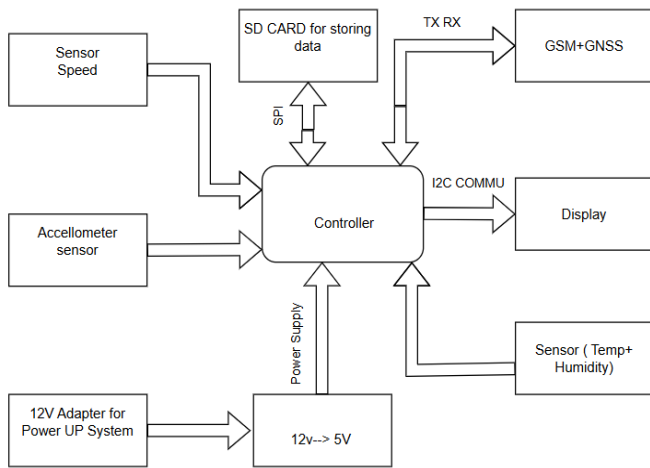


Fig 2: Generalized Black Box system

D. Comparative Analysis of Related Works and Proposed Technology

I. System Architecture

Related works predominantly employ prototype-level architectures based on development boards with loosely integrated modules. The proposed technology adopts a modular, ESP32-based hardware–software co-design, enabling tighter integration, improved reliability, and scalability under automotive operating conditions.

II. Sensor Coverage Most surveyed systems rely on limited sensing, typically accelerometers and GNSS modules, resulting in incomplete event context. The proposed system integrates multi-sensor inputs including GNSS, IMU, optical speed sensing, and environmental sensors, providing comprehensive vehicular and contextual data.

III. Crash Detection Approach Existing systems mainly implement simple threshold-based crash detection using single-axis or magnitude-based acceleration values, leading to frequent false positives. The proposed system employs multi-axis acceleration evaluation with continuous monitoring, reducing false triggers and improving detection robustness.

IV. Pre-Event and Post-Event Data Logging

Literature shows that most black box implementations record only event-based data, limiting accident reconstruction capability.

The proposed system uses circular buffer–based continuous logging to preserve both pre-crash and post-crash data for forensic analysis.

V. Data Storage Reliability

Related works commonly use SD card storage without redundancy, integrity checks, or fault tolerance, risking data loss during crashes or power failure. The proposed technology structures, time-stamps, and securely logs data, emphasizing forensic reliability and long-term data preservation.

VI. Communication and Emergency Alerting

IoT-based systems in the literature support GSM/GPS alerting but are often dependent on cloud availability and lack fail-safe mechanisms.

The proposed system integrates GSM-based emergency communication with GNSS-assisted location accuracy to ensure timely alert transmission during critical events.

VII. Data Security and Tamper Resistance

Many surveyed studies neglect data integrity, making recorded data vulnerable to manipulation or spoofing. The proposed architecture incorporates structured logging and integrity-focused design principles, aligning with forensic and legal admissibility requirements.

VIII. Processing Capability and Real-Time Performance

Existing systems often struggle with real-time performance due to limited processing resources and inefficient task scheduling.

The proposed ESP32-based dual-core processing framework enables concurrent data acquisition, crash detection, logging, and communication with low latency.

IX. Hardware Integration and Automotive Suitability

Literature largely reports fragmented sensor integration and minimal attention to EMI/EMC, thermal, and electrical robustness.

The proposed system emphasizes integrated PCB-level design and regulated power management to improve automotive-grade suitability.

X. Scalability and Future Expansion

Most existing designs offer limited scalability and lack provisions for advanced features. The proposed technology is designed to support future integration of AI-based crash detection, enhanced security mechanisms, and ADAS/V2X compatibility.

E. Expected Results of the Proposed Automotive Black Box System

Table III. Expected Results of the Proposed Automotive Black Box System

Performance Metric	Expected Outcome	Reasoning / Basis
Accident Detection Accuracy	High	Multi-sensor integration (IMU, GNSS, speed) improves event identification
False Positive	Reduced	Multi-axis acceleration

Rate		analysis filters non-crash disturbances
Emergency Response Time	Significantly reduced	GSM-based real-time alerting with GNSS location
Forensic Data Quality	Improved	Continuous pre- and post-event logging using circular buffer
Data Reliability	High	Structured, time-stamped non-volatile storage
System Latency	Low	ESP32 dual-core supports concurrent real-time tasks
Automotive Suitability	Improved	Regulated power design and integrated hardware architecture

The proposed automotive black box system is expected to demonstrate improved performance across key evaluation metrics when compared to existing solutions reported in the literature. Multi-sensor data acquisition and continuous logging are anticipated to enhance accident detection accuracy and forensic usefulness. Real-time GSM-based communication is expected to reduce emergency response time, while the ESP32-based processing architecture supports low-latency operation. Furthermore, the modular and integrated hardware design improves automotive suitability and scalability, enabling future extensions toward intelligent safety and forensic applications.

F. Conclusion:

This survey reviewed the evolution of automotive black box systems from basic event recorders to intelligent, connected platforms. While advances in inertial sensing, GNSS positioning, and wireless communication have improved capabilities, many systems still suffer from limited sensors, event-only logging, and weak security. Comparative analysis shows that multi-sensor acquisition and continuous pre-event logging are critical for accurate accident reconstruction, yet data integrity, tamper resistance, and hardware reliability remain inadequately addressed.

To overcome these issues, a modular ESP32-based architecture is proposed, offering real-time processing, structured logging, reliable emergency communication, and improved hardware integration. This low-cost approach enhances detection accuracy, response time, and forensic reliability while remaining scalable.

The survey concludes that future automotive black boxes should integrate multi-sensor fusion, secure data handling, and robust hardware to improve road safety, support legal investigations, and enable intelligent transportation systems.

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Smart Thermal-Aware Battery Management System

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Abstract— The growing adoption of lithium-ion batteries in electric vehicles and advanced electronic systems has increased the need for reliable and thermally stable battery operation. Battery packs often experience uneven temperature distribution, faster aging, and in extreme cases thermal runaway, which can negatively affect system performance and safety. To address these challenges, this paper proposes a Smart Thermal-Aware Battery Management System (ST-BMS) aimed at improving safety, maintaining temperature balance, and enhancing overall energy utilization.

The proposed system employs distributed temperature sensors to continuously monitor thermal conditions across the battery pack. Thermal data collected from these sensors is analyzed using a hybrid prediction approach that combines conventional thermal modeling techniques with machine-learning-based forecasting. For effective thermal regulation, the control strategy integrates proportional–integral–derivative (PID) control with rule-based logic and adaptive fuzzy control methods. In addition, machine learning algorithms such as Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks are applied to predict thermal behavior and detect potential anomalies at an early stage.

Simulation experiments conducted in MATLAB/Simulink demonstrate that the proposed ST-BMS significantly reduces thermal stress within the battery pack, prevents the formation of localized hot spots, improves energy efficiency, and contributes to a longer battery service life. The results indicate that the ST-BMS provides a robust and intelligent approach for ensuring safe and efficient operation of advanced battery systems.

Keywords— *Battery Management System (BMS); Smart Thermal-Aware System; Lithium-Ion Batteries; Thermal Runaway Mitigation; Temperature Monitoring; Predictive Modeling; Machine Learning; PID Control; Long Short-Term Memory (LSTM); Energy Efficiency; Electric Vehicles.*

I. INTRODUCTION

To Rising environmental concerns and the need to reduce greenhouse gas emissions have led to increased interest in **electric vehicles (EVs)** and **hybrid electric vehicles (HEVs)**. Unlike conventional vehicles that depend on internal combustion engines, EVs operate using rechargeable batteries

and can utilize electricity produced from renewable sources such as solar and wind energy. This transition supports cleaner transportation and better energy utilization [8].

Among the available battery technologies, **lithium-ion (Li-ion) batteries** are commonly used in EVs because of their high energy density, longer service life, and reliable performance. However, the overall efficiency and safety of these batteries are strongly influenced by the charging method applied during operation [6]. Therefore, selecting an appropriate charging strategy is necessary to maintain battery performance and durability. The charging method is an important part of the **Battery Management System (BMS)** in electric vehicles. A well-designed charging process “helps protect the battery from damage, improves operating efficiency, and extends” battery life [4]. At the same time, charging conditions must be properly controlled since long charging durations reduce user convenience, while very fast charging can result in energy losses and performance degradation [2].

Rising Temperature of battery during charging process is a critical aspect. When a battery is charged with a high current, additional heat may be generated, which can speed up battery degradation and may lead to hazardous conditions such as thermal runaway [1], [5]. Therefore, factors such as charging duration, energy efficiency, and proper temperature management must be considered while designing a battery charging system [7].

II. PROBLEM STATEMENT

A. Background and Motivation

Lithium-ion batteries are widely used in electric vehicles, portable electronic devices, and renewable energy storage systems. As the need for higher power and longer usage increases, these batteries experience more stress during operation, mainly due to the rise in temperature. If the heat generated inside the battery is not controlled properly, it can reduce battery performance, shorten its life, and in some cases may even cause safety problems such as thermal runaway or fire.

B. Limitations of Existing BMS

Conventional Battery Management Systems (BMS) are primarily designed to supervise electrical variables such as

voltage, current, and state of charge in order to ensure proper battery operation. Although this approach supports electrical safety and performance control, it generally provides limited emphasis on thermal monitoring and predictive analysis. Consequently, temperature-related issues such as uneven heat distribution, the emergence of localized hot spots, and delayed thermal regulation may not be detected at an early stage. Under conditions such as rapid charging or high power demand, these thermal irregularities can accelerate battery wear and increase the probability of system malfunction or failure.

C. Need for a Thermal-Aware System

Safe battery operation requires continuous monitoring of its thermal conditions during use. Any abnormal increase in temperature should be identified at an early stage so that preventive measures can be taken before the temperature reaches critical limits. Incorporating predictive analysis along with automated control mechanisms improves the reliability of the system and helps prevent failures that may occur due to sudden load variations or adverse environmental conditions.

D. Problem Definition

A **Smart Thermal-Aware Battery Management System** is therefore required to perform the following functions:

- Predict overheating using thermal models or algorithms.
- Continuously monitor temperature across battery cells in real time.
- Maintain uniform temperature distribution across the battery pack.
- Operate as a low-cost, efficient, and scalable solution suitable for various applications.

III. SYSTEM DEVELOPMENT PROCESS

The development of the proposed **Smart Thermal-Aware Battery Management System (ST-BMS)** was carried out in a structured and systematic manner to ensure reliable thermal monitoring, prediction, and control. The development process consists of hardware design, sensing architecture, data acquisition, thermal modeling, and intelligent control implementation.

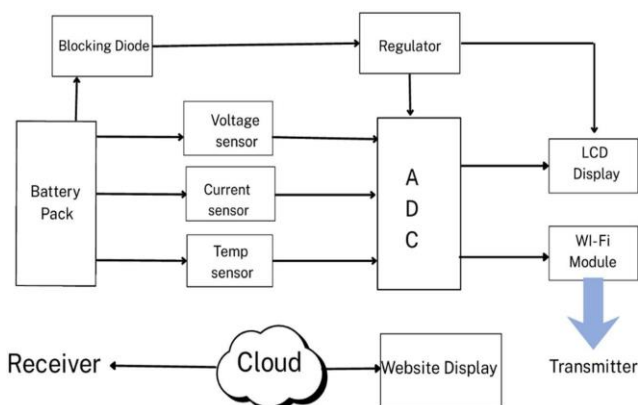


Fig. 1 IoT Based Battery Monitoring System

A. System Architecture Design

The **Smart Thermal-Aware Battery Management System (ST-BMS)** is developed to monitor and control the temperature

conditions of lithium-ion battery packs during operation. The system consists of several key elements, including temperature sensors, a data acquisition unit, a processing controller, and a thermal regulation mechanism. Temperature sensors are installed at different locations within the battery pack to measure the temperature of individual cells in real time. The measured values are sent to a central controller, where the information is examined and used to determine suitable control actions.

B. Temperature Sensing and Data Acquisition

To track temperature properly, multiple sensors are placed at different points in the battery pack. These sensors measure the temperature of each cell and send the data to the microcontroller. The system collects this data at regular intervals and prepares it for analysis. Continuous temperature monitoring helps in identifying rising heat levels, detecting hot spots, and checking if the heat is evenly distributed across all battery cells.

C. Thermal Data Processing

The temperature data collected from the sensors is processed by the system to understand how the temperature is changing over time. The system compares these values with the safe temperature limits of the battery. If the temperature starts moving toward unsafe levels, the controller takes the required action to control it. This helps keep the battery working within a safe temperature range and ensures proper operation.

D. Integration of Prediction Algorithms

The system also uses methods like **SVM** and **LSTM** to study the temperature data. These methods use both previous data and current readings to understand the pattern of temperature changes. Based on this, the system can guess how the temperature may change in the future. This helps in identifying problems early, so the system can take action before the temperature becomes too high, ensuring safe and smooth battery operation.

E. Thermal Control Mechanism

After the continuous monitoring of temperature data and predicting possible temperature changes, the controller takes the required steps to control the battery temperature. The system uses a PID controller along with fuzzy logic to operate cooling devices such as fans or heat sinks. This helps keep the battery temperature balanced across the battery pack and reduces overheating during operation.

IV. METHODOLOGY

The proposed system estimates the **State of Charge (SOC)** of the battery using the **coulomb counting technique**, which is widely used in battery management systems due to its simplicity and low computational requirement. This method determines the battery charge level by integrating the current flowing into and out of the battery over a period of time. The accumulated charge is expressed in ampere-hours (Ah), allowing the system to estimate the remaining battery capacity. The accuracy of this approach depends mainly on precise current measurement and continuous monitoring of the charge flow.

The process begins with the initialization of the coulomb counting module within the controller. During startup, the system resets the voltage reference and initial charge parameters to zero to ensure proper calibration. After initialization, communication is established between the Arduino microcontroller and the sensing components responsible for monitoring battery parameters.

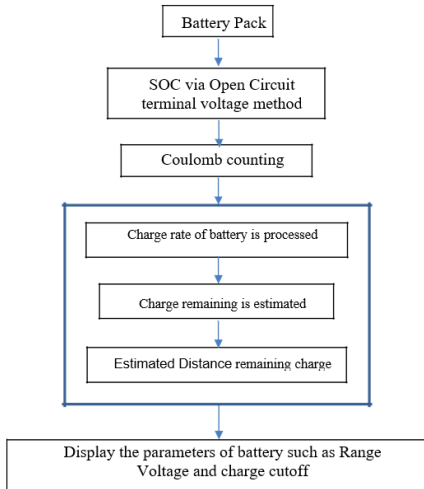


Fig. 2 Proposed Control Scheme

A. Current Measurement and Data Acquisition

After the communication between all the system components is properly established, the battery is connected to a load so that current can start flowing through the circuit. During this process, the coulomb counter continuously measures the current passing through the battery. This measured data is then sent to the Arduino controller for further use. Since the sensors provide output in analog form, the Arduino cannot use this data directly. Therefore, it converts the analog signals into digital values using its built-in Analog-to-Digital Converter (ADC). Once the data is converted into digital form, it becomes easier to process, analyze, and store. This processed information is then used by the system for monitoring and controlling the battery operation effectively.

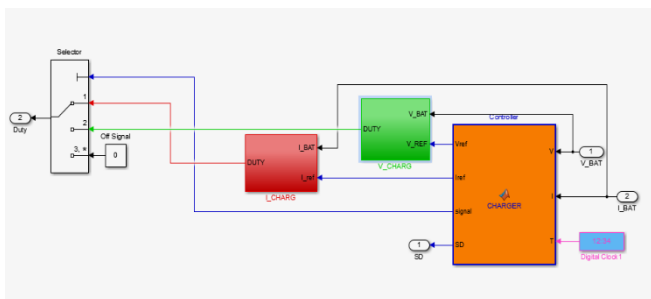


Fig. 3 Voltage and current control section

B. State of Charge Calculation and Monitoring

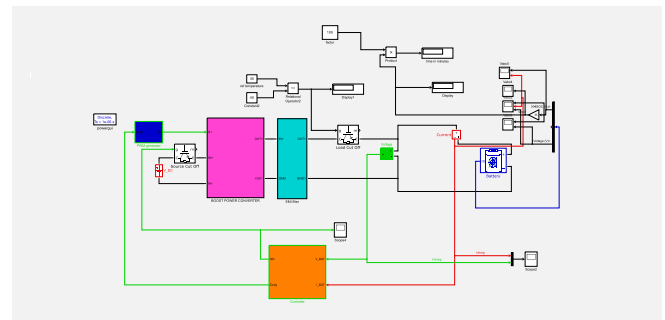
The system uses the processed data to keep checking the battery's State of Charge (SOC) by tracking how much charge is going in and out of the battery. The SOC value is updated continuously and shown on the display, so the user can easily see the battery condition. When the battery level comes close to a safe limit, the system gives an alert to inform the user.

C. Charging Control and Safety Operation

When the battery is connected for charging, the coulomb counting process is paused until charging is complete. During discharge, the system continuously checks the battery condition and gives alerts to prevent problems like deep discharge. Once the battery is fully charged, the coulomb counter starts again with the continuous monitoring of battery.

V. RESULTS AND DISCUSSIONS

The CC–CV charging algorithm was implemented using MATLAB/Simulink to study the system behavior before carrying out the hardware implementation. The simulation model consists of the DC–DC converter, the control logic, and the battery charging model. In this model, the duty cycle of the PWM signal is adjusted according to the measured voltage and current values so that the charging process can be properly controlled. The simulation output shows the changes in battery voltage, charging current, and the estimated State of Charge



(SOC) throughout the charging process.

Fig. 4 Simulation window

The simulation results demonstrate the battery behaviour during the charging process using the CC–CV charging technique. The charging current and the State of Charge (SOC) were observed to assess the system performance. Fig. 5 shows the temperature variation of the EV battery recorded through the monitoring system. The temperature data is collected using a sensor connected to the controller and transmitted to the cloud platform for visualization. Under normal operating conditions, the battery temperature remains within a safe range, indicating stable battery performance during charging and operation.

The graph also highlights the importance of temperature monitoring in battery management systems. Sudden changes or abnormal increases in temperature can indicate unsafe conditions such as overheating or excessive current flow. By continuously tracking the temperature, the system helps ensure safe battery operation and prevents possible damage to the battery pack.

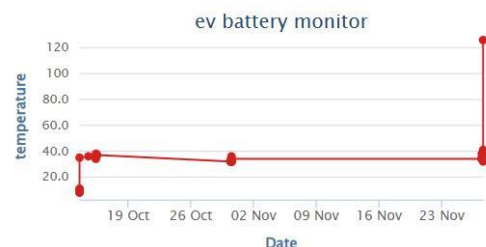


Fig. 5 Battery Temperature Monitoring

Fig. 6 illustrates the variation in battery voltage observed during the monitoring period. The voltage readings are obtained through the sensing circuit and transmitted to the monitoring platform for analysis. The graph shows that the voltage remains relatively stable with small variations during

the charging and operating conditions.

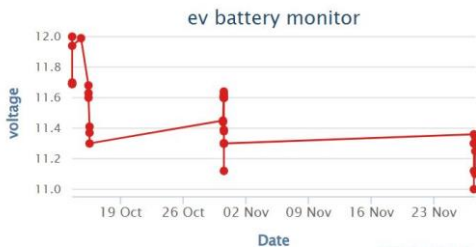


Fig. 6 State-Of-Charge

Keeping track of the battery voltage is important to understand how the battery is charging and how well it is working. When the voltage stays steady, it shows that the charging circuit and converter are working properly. Regularly checking the voltage also helps in estimating values like the State of Charge (SOC) and ensures the battery operates safely.

A hardware setup was developed to validate the simulation results under real operating conditions. The system consists of an Arduino microcontroller, a DC–DC buck converter, current and voltage sensors, and a lithium battery. The Arduino monitors key battery parameters and controls the charging process. The buck converter regulates the input voltage to provide the required charging level. Based on the sensor readings, the controller adjusts the PWM signal to maintain proper CC–CV charging. The hardware results were then compared with the simulation results to evaluate the overall



system performance.

Fig. 7 Hardware Prototype

VI. HARDWARE DESIGN CALCULATIONS

A. Output Voltage of Buck Converter

The output voltage of a buck converter depends on the duty cycle of the PWM signal.

$$V_o = D \times V_{in}$$

Where,

V_o = Output voltage

V_{in} = Input voltage

D = Duty cycle

B. Inductor Value Calculation

$$L = \frac{(V_{in} - V_o) \times D}{f_s \times \Delta I_L}$$

Where,

L = Inductor value

f_s = Switching frequency

ΔI_L = Inductor ripple current

C. Output Capacitor Calculation

$$C = \frac{\Delta I_L}{8 \times f_s \times \Delta V_o}$$

Where,

C = Output capacitor

ΔV_o = Output voltage ripple

D. Battery Charging Power

$$P = V \times I$$

VII. APPLICATIONS

A. Electric Vehicles (EVs)

Battery packs in electric vehicles often operate under high current demand and fast charging conditions, which can lead to significant heat generation. Therefore, effective thermal management is essential to ensure safe and reliable operation. The proposed ST-BMS continuously monitors the battery temperature and facilitates timely regulation of heat levels. This helps maintain the system within safe operating limits and reduces the risk of thermal instability.

B. Renewable Energy Storage Systems

In solar and wind energy systems, batteries play an important role in storing power. If the temperature is not controlled, it can affect their performance. The ST-BMS checks the battery temperature and helps keep it stable, so the system runs smoothly and safely.

C. Consumer Electronics

Devices like smartphones, tablets, and laptops use lithium-ion batteries for their operation. If the battery gets too hot, it can reduce performance and shorten its life. By checking and controlling the temperature, the system helps the device run smoothly and keeps the battery in good condition for a longer time. It also helps prevent damage and makes the device safer to use.

VIII. FUTURE WORK

Although the proposed Smart Thermal-Aware Battery Management System (ST-BMS) shows good performance in simulation, there is still scope for further improvement. In future work, the system can be implemented on a real hardware setup to evaluate its performance under practical operating conditions. This will help in validating the simulation results and understanding real-time challenges. The system can also be

tested under different environmental conditions and varying load scenarios to ensure reliable operation in real-world applications.

Further improvements can be made by using more accurate sensors and better calibration techniques to enhance measurement accuracy. The control algorithm can also be refined to respond more quickly to sudden temperature changes, improving system safety. In addition, integrating Internet of Things (IoT) technology can enable remote monitoring and real-time tracking of battery parameters. The system can also be optimized to reduce power consumption and extended to support different battery types and larger battery packs used in electric vehicles. These enhancements will improve the overall efficiency, reliability, and practical usability of the system.

IX. CONCLUSION

This paper presents a **Smart Thermal-Aware Battery Management System (ST-BMS)** developed to improve the safety, reliability, and operational efficiency of lithium-ion battery systems. The proposed approach combines distributed temperature sensing, thermal prediction techniques, and intelligent control methods to observe and manage battery temperature during operation.

Machine Methods like **SVM** and **LSTM** are used to study how the battery temperature changes and to get an idea of how it might behave next. This helps the system notice early signs of overheating so that action can be taken in time. To control the temperature, a combination of **PID control and fuzzy logic** is used to operate cooling devices and keep the temperature steady. From the simulation results, it is seen that the system is able to keep the temperature within safe limits and reduce the chances of hot spots. Continuous monitoring and prediction help the battery work more smoothly, reduce stress on it, and improve its life and performance.

Table (1) Performance Analysis

Parameter	Simulation	Hardware
Voltage	12.9 V	11.7 V
Current	5.0 A	4.8 A
Time	30 Min	28 Min

The simulation analysis carried out using MATLAB/Simulink shows that the developed system helps control temperature variations within the battery pack. It minimizes thermal stress, prevents localized heating, and promotes uniform temperature distribution among cells. These improvements support safer battery operation, longer battery durability, and better energy efficiency

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Automated Identification and Severity Assessment of Brain Tumors from MRI Scans Using Advanced Deep Neural Networks

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Abstract— Brain tumors: a rapid and to be able to make an appropriate diagnosis, it is important to effectively arrange treatments and improved patient survival. This paper presents a D L based automated system as a means of categorizing brain tumors and staging using magnetic resonance imaging (MRI) data implemented in MATLAB. The proposed approach employs a transfer learning strategy using a pretrained ResNet-50 convolutional neural network to get out discriminative characteristics from brain MRI pictures. Prior to grouping, comprehensive to increase image quality and model generalization, preprocessing methods such as scaling, normalization, denoising, and data augmentation are used. The technique estimates tumor severity levels while categorizing MRI images into meningioma, glioma, pituitary tumor, or normal categories. Standard measures such as F1-score, confusion matrix, accuracy, precision, recall, and receiver operating characteristic (ROC) analysis are used in order to assess performance. Experiments show that the suggested model outperforms traditional techniques and delivers dependable staging performance and high classification accuracy, confirming its applicability for computer-aided clinical decision support systems.

Keywords— Brain Tumor, Deep Learning, CNN, MRI, Transfer Learning, MATLAB.

I. INTRODUCTION

One of the most dangerous neurological disorders is the brain tumor, which often causes high mortality and long-term disability when not diagnosed and treated at an early stage [1], [2]. A brain tumor is characterized by uncontrolled growth of abnormal cells within brain tissue and may be either benign or malignant depending on its nature and rate of growth [3], [4]. The rising number of brain tumor cases worldwide has increased the need for accurate diagnosis and timely treatment [5]. Early identification of the disease improves survival, supports treatment planning, and lowers the possibility of permanent neurological damage [6], [7]. However, because of the complex structure of the brain and the unclear appearance of tumors during the initial stage, diagnosis remains difficult for medical experts [8].

Magnetic Resonance Imaging (MRI) is widely used for brain tumor analysis because it is non-invasive and provides excellent soft-tissue contrast and clear localization of abnormal regions [9]. MRI helps in identifying tumor size, shape, location, and the involvement of nearby tissues [10]. Even though MRI provides detailed information, its interpretation depends greatly on the experience of radiologists, which may lead to differences in diagnosis and variations between observers [11], [12].

Problem Statement

Accurate diagnosis and staging of brain tumors from MRI images is difficult because of the complex brain structure and variation in tumor appearance. Manual interpretation by radiologists is time-consuming and may lead to diagnostic differences and errors [1], [2].

Objectives of the study

1. To study the use of deep learning for brain tumor classification using MRI images.
2. To study the effect of preprocessing techniques on classification accuracy.
3. To study the performance of the pretrained ResNet-50 model for feature extraction.
4. To study the ability of the system to classify tumor types and estimate severity.
5. To study the performance of the proposed model using standard evaluation metrics.

Scope of the study

All that is included in this study is the categorization and staging of brain tumors use two-dimensional MRI img. A system focuses on These four types of tumors are Gliomas, meningiomas, pituitary tumors, and normal cases, using a method based on deep learning implemented in MATLAB.

II. LITERATURE SURVEY

[1] Multi-Classification of Brain Tumor Images Using Deep Neural Network

Authors: Hossam H. Sultan, Nancy M. Salem, and Walid Al-Atabany

Publication: *IEEE Access*, 2019

Summary: This work proposed a methodology for utilizing deep learning to categorize brain tumors into numerous neural networks using MRI images.

[2] Deep Learning for Multigrade Brain Tumor Classification in Smart Healthcare Systems: A Prospective Survey

Authors: Khan Muhammad, Salman Khan, Javier Del Ser, and Victor Hugo C. de Albuquerque

Publication: *IEEE Transactions on Neural Networks and Learning Systems*, 2021

Summary: This survey systematically reviewed DL pipelines to categorize brain tumors, covering preprocessing, feature learning, classification strategies, and evaluation practices.

[3] Brain Tumor Identification and Classification of MRI Images Using Deep Learning Techniques

Authors: Zheshu Jia and Deyun Chen

Publication: *IEEE Access*, 2020 (DOI available)

Summary: In this research, a DL method for tumor finding and categorization in the brain to MRI img, focusing the automated feature extraction and classification through modern deep architectures.

[4] Brain Tumor Classification Using the Modified ResNet50 Model Based on Transfer Learning

Authors: A. K. Sharma *et al.*

Publication: *Biomedical Signal Processing and Control*, 2023

Summary: This paper enhanced ResNet-50 in order to classify brain tumors using transfer learning applied to architectural or training-level modifications to improve discrimination capability. The work highlights how ResNet-style residual learning can improve feature depth and training stability, especially in medical datasets with limited labeled images.

III. PROPOSED SYSTEM

The proposed system presents the automatic framework a brain tumor detection, segmentation, classifying, and staging using (MRI) data. The system integrates image preprocessing, optimization-based segmentation, and deep learning-based classification to achieve accurate and reliable diagnostic performance.

A. System Flow

An illustration of the proposed system's overall workflow in Fig. 3.1, and it consists of sequential stages from data acquisition to final classification output.

I. System Initialization

The process begins with system initialization, where the MATLAB environment and required deep learning libraries are configured for data processing, training, and evaluation.

II. Load MRI Dataset

Brain MRI images are loaded from the dataset and organized according to their respective class labels. These images form the input data for training, validating, and testing the DL model.

III. Dataset Splitting

To guarantee objective learning and assessment, the dataset is separated into 3 parts:

- **Training Set:** A tool for figuring out model parameters to change hyperparameters and avoid overfitting, use the validation set.
- **Test Set:** Used to see how well the finished model works on unknown data

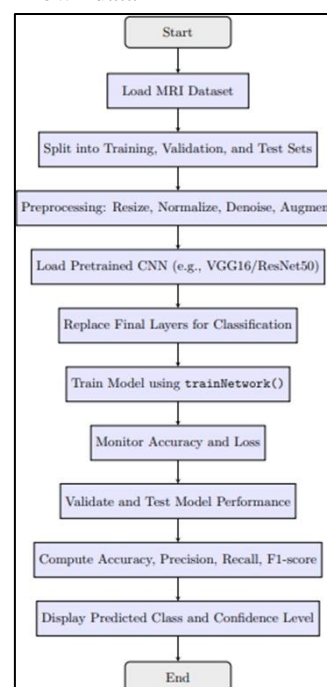


Fig.1 System Flow

B. Image Pre-processing

Image pre-processing is applied to make the data better and guarantee uniformity throughout the collection. The pre-processing stage includes:

- **Resizing:** All MRI images are resized to uniform dimensions compatible with the CNN input layer
- **Normalization:** For training purposes, pixel intensity data are normalized to speed convergence.
- **Denoising:** Noise reduction techniques are applied to suppress imaging artifacts
- **Data Augmentation:** To make datasets more diverse and to make models more generalizable, methods including scaling, flipping, and rotating are used.

IV. SYSTEM DESIGN

A. Input Acquisition

The system begins with input acquisition, where the user selects a brain MRI image standard picture formats as well

as JPG, PNG, or BMP. The selected image is loaded into the MATLAB workspace and serves as the primary input for subsequent processing stages.

B. Pre-Processing

Pre-processing is applied to enhance image quality and ensure consistency across MRI inputs.

1. Grayscale Conversion:

If the data that is MRI image is in RGB tray, it is converted into grayscale to simple processing and reduce computational complexity.

2. Noise Filtering:

A median screening technique is used for remove speckle noise and minor artifacts commonly present in MRI images while preserving important edge information.



Fig.2 System Architecture

C. Brain Extraction

To isolate the brain region from background and skull areas, a brain extraction module is applied.

D. Tumor Segmentation

Tumor segmentation is performed on the extracted brain region using adaptive thresholding techniques. The resulting binary tumor mask is refined through morphological cleanup operations, including hole filling and removal of small connected components. This step ensures accurate separation of the tumor region from healthy brain tissues.

E. Feature Extraction

Quantitative features describing the tumor's geometric and structural properties are extracted using region-based analysis. The extracted features include:

- Tumor area
- Solidity
- Eccentricity
- Equivalent diameter

These features provide essential information for tumor classification and staging.

F. Tumor Classification

Tumor classification is performed using a rule-based decision logic derived from extracted shape features. Based on solidity and eccentricity values, the tumor is categorized as:

- Pituitary tumor
- Glioma
- Meningioma

This logical classification approach enables efficient differentiation between tumor types based on morphological characteristics.

G. Tumor Staging

Tumor staging is determined by calculating the ratio of tumor area to total brain area. Based on this ratio, the tumor severity is classified into four stages:

- Stage I: Tumor area < 0.8%
- Stage II: Tumor area < 1.8%
- Stage III: Tumor area < 3.5%
- Stage IV: Tumor area ≥ 3.5%

This staging provides clinically meaningful insight into tumor progression.

V. ALGORITHMS USED

A. Genetic Algorithm for Tumor Region Optimization

The Genetic Algorithm is an evolutionary optimization technique inspired by natural selection principles. In the proposed system, GA is applied to optimize tumor region segmentation by improving boundary accuracy and intensity consistency.

B. Deep CNN (ResNet-50) for Classification and Staging

ResNet-50 is a deep CNN consisting of remaining blocks that enable stable training of deep architectures. In this work, transfer learning is employed by adapting a pretrained ResNet-50 model for classifying brain tumors.

C. Performance Evaluation Algorithm

Diagnostic dependability is assessed by evaluating the trained model using conventional classification metrics.

D. Performance Evaluation

1) Matthews Correlation Coefficient(MCC)

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Range: -1 to +1

- +1 →perfect prediction
- 0 →random
- -1 →totally wrong

2) Cohen's Kappa Coefficient(K)

$$K = \frac{P_o - P_e}{1 - P_e}$$

Where:

$$P_o = \frac{TP + TN}{N}$$

$$P_e = \frac{(TP + FP)(TP + FN) + (FN + TN)(FP + TN)}{N^2}$$

3) ROC-AUC(Receiver Operating Characteristics)

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN}$$

$$AUC = \int_0^1 TPR(FPR)d(FPR)$$

Interpretation

- AUC=1→Perfect
- AUC > 0.9 →Excellent

5) Tumor Stage Classification Consistency Index

$$SCI = 1 - \frac{|S_{pred} - S_{actual}|}{S_{max}}$$

Where,

- S_{pred} = predicted stage
- S_{actual} = expert stage
- S_{max} = 4

6) Computational Efficiency

$$T_{avg} = \frac{1}{N} \sum_{i=1}^N t_i$$

$$FPS = \frac{1}{T_{avg}}$$

7) Confusion Matrix

The confusion matrix evaluates the classification performance by representing true positives, true negatives, false positives, and false negatives. It is used to compute metrics such as accuracy, precision, recall, and F1-score, providing insight into the model’s effectiveness and reliability in tumor detection.

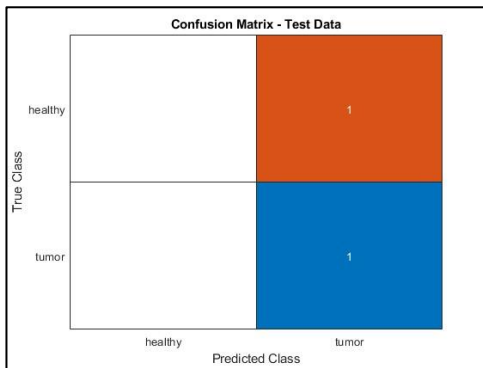


Fig.3 Illustrates the confusion matrix obtained for the proposed model.

8) ROC Curve and AUC

The (ROC) curve is used to evaluate considering both classifier's sensitivity and specificity at various thresholds levels.

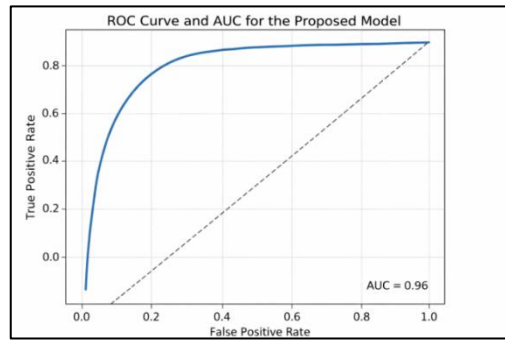


Fig.4 ROC Curve and AUC for the Envisaged Model

9) Training Curves

Validation and training accuracy curves are examined to examine the DL model's learning behavior.

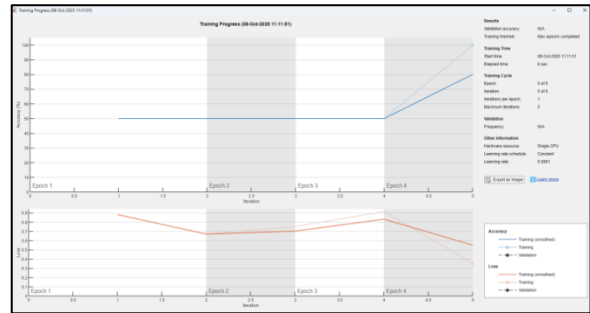


Fig.5 Training Progress Graph

10) Comparison with Existing Models

In order to prove that the strategy is working, its performance is juxtaposed with previously reported brain tumor classification techniques. The comparison highlights the superiority of the ResNet-50-based model in terms of classification accuracy and robustness.

Sr. No.	Technique	Accuracy (%)
1	Thresholding Method	47.6
2	Basic CNN Classifier	51.1
3	Hybrid Genetic Method	67.3
4	Proposed ResNet-50 Model	91.0

The comparison confirms that the proposed deep learning-based approach significantly outperforms traditional image processing and basic CNN models, validating its suitability for accurate brain tumor classification and staging.

VII. RESULTS AND ANALYSIS

A. Experimental Setup

The proposed system was implemented in MATLAB using deep learning and image processing techniques on brain MRI images. Preprocessing methods were applied before testing the system for tumor detection, classification, and staging.

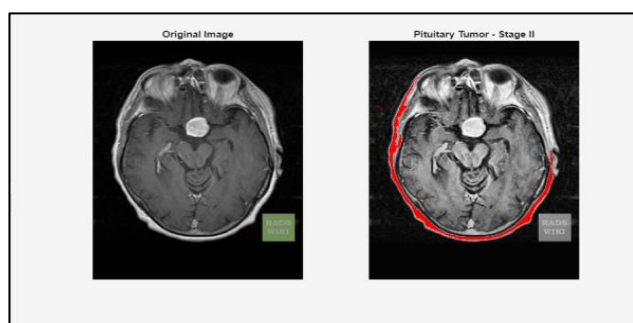


Fig 6: Tumor detection and segmentation result

B. Tumor Detection and Segmentation

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Command Window
===== FEATURES =====
|      Area: 33932
|      Centroid: [432.3090 875.4752]
|      Eccentricity: 0.8120
|      Perimeter: 4.2319e+03
|      Ratio: 0.0452
Tumor Type: Pituitary Tumor
Tumor Stage: Stage II

```

Fig 7: Extracted tumor features and classification output

The proposed method successfully detects and segments the tumor region from MRI images. Features such as area, centroid, perimeter, eccentricity, and tumor-to-brain area ratio are extracted for classification and severity analysis.

D. Tumor Classification

The developed model classified the detected brain tumor from the MRI image. In the tested sample, the tumor was recognized as a pituitary tumor.

E. Tumor Staging

Tumor stage was estimated using the ratio between tumor area and total brain area. This helps determine the severity of the disease.

G. Overall Performance Discussion

The proposed method successfully detected, classified, and staged brain tumors from MRI images. The combination of image processing and deep learning improved the accuracy and reliability of the system.

VIII. CONCLUSION

This paper presented an automated brain tumor classification and staging system using MRI images based on deep learning techniques implemented in MATLAB. The proposed approach effectively integrates image preprocessing, segmentation, feature extraction, and transfer learning with a ResNet-50 convolutional neural network to achieve accurate tumor identification and severity assessment. Experimental results demonstrate high classification accuracy and reliable staging performance, confirming the effectiveness of the system for computer-aided diagnosis.

IX. FUTURE SCOPE

Adding three-dimensional (3D) MRI volumes to the proposed brain tumor classification and staging system could make it even better by giving it more spatial information and making it easier to find tumors. Combining different types of MRI data, like T1, T2, FLAIR, and contrast-enhanced images, can give a more complete picture of a tumor and make staging more reliable.

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A Novel System for Recommending Agricultural Crops Using Machine Learning Approach

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Abstract— Farmers play a crucial role in our lives. It takes usually a couple of months in advance for a crop recommendation system to predict crop yields for improved production. Crop prediction is dependent on the use of computer programs that describe in quantifiable terms the interactions between plants and their environment, as well as their soil characteristics. It is first necessary to collect a soil sample from the field for soil testing. The Maharashtra state's agricultural production is decreased as a result of uncertainty caused by its coastal location. Productivity should increase as population and area grow, but it cannot. As a result of climatic factors, farmers are no longer able to use word-of-mouth. Farmers can benefit from good agricultural information thanks to the growth of IT in the world. Therefore, in this present climate, there is a need for intelligent use of modern technology in the agribusiness sector. Crop prediction is a challenging task for farming because it depends on feature selection and classification. Using a novel framework is proposed for choosing crop characteristics, assessing crop yields through classification. The categorization algorithms employed in this approach differ from those used in other research, as they employ multiple prediction methods.

Keywords—Agriculture, Crop Prediction, Classification, Machine Learning, Segmentation

I. INTRODUCTION

There are few countries in the world that still practice agriculture as old as India. As a result of globalization, agriculture trends have changed dramatically in recent years. In India, agriculture has been adversely affected by a variety of factors. Health has been regained through the development of many new technologies. The use of precision agriculture is one such technique. India is experiencing a boom in precision agriculture.

"Site-specific" farming is precision agriculture. The technology has helped to achieve efficient inputs, outputs, and better decisions as far as farming is concerned. There are many systems available that can determine the inputs for

a specific plot of land. Precision agriculture has brought about some improvements, but it has still faced some issues. In addition to crops and fertilizers, systems can also suggest farming techniques. Precision agriculture involves the recommendation of crops. Various parameters are taken into account when recommending crops.

The economy of a country is dramatically impacted by agriculture. Natural factors are causing Agriculture farming to degrade in modern times. It is directly dependent on the environmental factors such as sunlight, humidity, soil type, rainfall, maximum and minimum temperatures, crop fertilizers, pesticides, etc. To flourish in Agriculture, one need knowledge of proper harvesting. India has seasons:

1. From December to March, there is winter
2. From April to June, there is Summer
3. Between July and September is monsoon season
4. During October and November, the post-monsoon season occurs.

Various seasons and rainfall make it necessary to determine which crops are suitable for cultivation. The management of crops, the production of crops, and the productivity from the crops pose major challenges to farmers. As more and more young people are interested in agriculture these days, farmers and cultivators need proper assistance regarding crop cultivation. Assessment of real-world problems by IT sector is increasing at a faster rate. The amount of data in agriculture is increasing every day. Agricultural data can be accessed with the advancement of the Internet of Things (IoT). In order to extract or use useful information from the spreading data on agriculture, there is a need for a system which analyzes agricultural data in an obvious way.

By combining data with machine learning techniques, we can develop a model that can be predicted based on the data. The solution to farming issues such as crop prediction,

rotation, water requirements, fertilizer requirements, and protection can be found here. A reliable method for crop cultivation and management is necessary since there are variable climatic factors in the environment. Agriculturalists can use this information to improve their farming. By using data mining, farmers can receive recommendations to grow their crops. Based on climatic and quantity factors, such an approach is implemented. Agricultural databases can be analyzed with Data Analytics. Based on productivity and season, the crop dataset has been analysed.

II. MOTIVATION

Farming plays an important role in everyday life.

Classification and feature selection play a crucial role in crop prediction in farming. The study predicts crop yield by selecting characteristics from a crop, which is then classified. Our study uses a number of categorization algorithms instead of just one prediction approach as has been used in other studies.

Rajeswari et al.[4] given as, Agriculture relies heavily on soil. Using data mining classification techniques, the work will predict soil type. Methods used are JRip, J48, and Naive Bayes are used to predict soil type through data mining classification techniques. Two types of soil are taken into consideration when using these classifier algorithms, namely Red and Black soils. This data can be better modelled using JRip and Kappa Statistics were raised in the forecast.

III. LITERATURE REVIEW

Shreya S. Bhanose, Kalyani A. Bogawar et al.[1] stated as , Farmers require support with their decisions to enhance the quality of their farming by utilizing well-defined and systematic approaches to predict crops and yields. Since crop knowledge-bases are not readily available, predicting the best crops is complex. Better quality farming and higher revenues can be achieved through crop prediction. To extract useful information and give predictions in the field of data mining, it is efficient to use data clustering. In the past, a number of approaches have been used for crop prediction. Making correct decisions with crop prediction model. Indeed, this helps farmers generate better revenue and improve farming quality. As a result of a random selection of an initial cluster center and a decision regarding the number of clusters, traditional clustering algorithms such as k-means, improved rough k-means make the task of clustering more complex. Due to the initial cluster-centric selection, the modified K-Means algorithm improves accuracy of a system.

Tripathy A.K et al.[2] elaborated, In developing countries like India, agriculture is one of the most important applications. Decisions related to agriculture are often based on data mining. Data mining is the process of extracting relevant knowledge from a set of data and converting it into a human- understandable format. Climate can have a huge impact on crop productivity in certain agriculture regions. Crop management depends on climatic conditions. In order to achieve good crop management, real-time weather data can be useful. In order to obtain knowledge and trends, information and communications technology can be used to

automate the extraction of significant data, which eliminates manual processes and makes it simpler to extract data directly from electronic sources. Producing less costs, increasing yields, and raising market prices can be achieved in this way. Data mining is also used in analyzing and predicting useful patterns from vast yet dynamically changing climatic data. Researchers and engineers have developed fuzzy logic, artificial neural networks, genetic algorithms, decision trees, and support vector machines for studying soil, climate conditions, and water regimes that affect crop growth and pest control. There is a summary as well of data mining techniques, neural networks, support vector machines, big data analysis, and soft computing in agriculture in this paper.

Ramesh Babu Palepu et al.[3] said that, In developing countries such as India, agriculture is a backbone for fulfilling global food demands. It is possible to improve cultivation yields by applying data mining techniques to agriculture, especially soils, by revising pledge making situations and improving pledges. Several issues related to agriculture require soil analysis for resolution. There are several data mining techniques discussed, along with their related work, by several authors in context to soil analysis in this paper. Soil analysis uses very current data mining techniques.

Vikas Kumar et al.[8] given in their paper, CT has become a primary need for humans due to the evolution of Web 2.0. Farmers lack agricultural knowledge. Farmers and experts can communicate through ICT. Using spatial data and agricultural knowledge bases, a semantic web architecture for generating agricultural recommendations is proposed by the authors. In response to climate conditions and geographic data, our knowledge base will send recommendations to farmers. In order to find out information regarding a specific crop, farmers send queries to a query engine. GIS data and crop knowledge bases may be accessed in a query. On a mobile device, the query's results are displayed.

Additionally, it was found that data mining aids in the analysis and prediction of useful patterns from vast and constantly changing climatic data. Fuzzy logic, artificial neural networks, genetic algorithms, decision trees, and support vector machines have been developed by agricultural and biological engineers to study soil, climate, and water conditions related to crop growth and pest management. This study summarizes the use of Soft Computing, Big Data analyses, Neural Networks and Support Vector Machines in the agriculture field based on weather conditions. [10].

TABLE I. REVIEW OF EXISTING METHODS

Author and Year	Methodology	Advantages	Limitations
Shreya Bhanose et al. [1] 2021	Modified K-Means algorithm	Improves Accuracy	Using limited training data, for training

Tripathy A.K et al.[2] 2019	ANN with Fuzzy system	Eliminates manual extraction of the data	Limiting parameters and their effects
Ramesh Babu Palepu et al.[3] 2019	Data Mining	Helps to Improve cultivation yields	Sample Size
Rajeswari et al.[4] 2018	JRip, J48 and Naïve Bayes	Easy classification will be done	Further improvement and reduction of computation time
A. Swarupa Rani et al. [5] 2020	Enhanced SVM	Elaborates the Application in terms of agricultural field	Memory limitations
Vikas Kumar et al.[8] 2021	IoT Based Web 2.0	Uses spatial data and agricultural knowledge bases	Not Applicable
Ramesh Medar et al.[11] 2019	Data Mining Techniques	Detailed Examination of the Various Techniques are carried out	More Computational time needed

IV. EXISTING METHODOLOGY

Using the data mining process, Tripathy et al. described how pesticides can be managed during crop cultivation. In order to apply a spatiotemporal analysis to crop estimation, Pritam Bose developed an SNN model. Modified k-means clustering algorithm was used by Shreya S. Bhamose[13] to predict harvest and water requirements for crops.

A. Drawbacks of Existing Approach

- There was no consideration of other parameters or states in the existing system.
- Build time is slower.
- Complicated.
- Costly from a computational point of view.

V. PROPOSED METHODOLOGY

A number of agricultural parameters influence crop production. A recommendation can be made to the farmer based on previous years' crop production. The farmer will be able to determine whether a certain crop has been yielding a good yield recently by this kind of suggestion. Several factors can reduce crop production, including crop disease, water problems, and many others. Farmers may be able to obtain useful information about the crop in high demand on the market during that year while examining the production. The farmer can use this information to determine the trend in crops in recent years. Based on the crop production season, farmers will receive recommendations.

A. Advantages of Proposed System

- As opposed to the existing system, which considers a single state, our proposed system considers all the states of India.

- It is possible to extract these recommendations for educating the farmers. Farmers are given a better understanding of crops to cultivate through pictorial representations.
- Normalization and scaling are not required
- Interpretation is simple and easy to understand

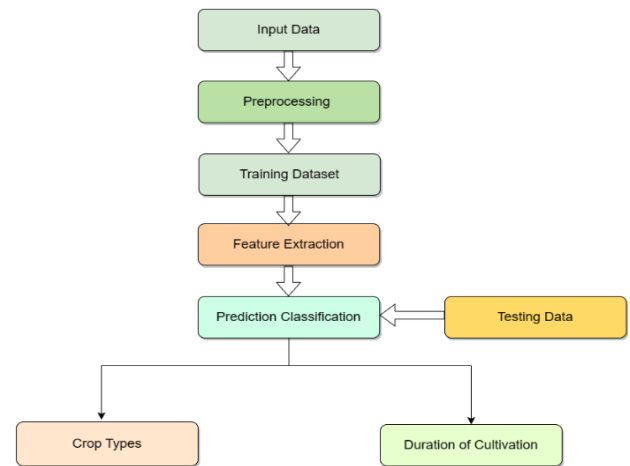


Fig. 1. Proposed Method

B. Machine Learning

Machine Learning is the process of learning from examples without being explicitly programmable. The purpose of machine learning is to predict an outcome that can be used to make useful decisions by combining data with statistical tools. Data-driven machines can produce accurate results by learning from data (i.e., example). A close relationship exists between machine learning and data mining. Using an algorithm, the machine formulates answers from data. Recommendations are typically provided by machine learning. In order to personalize recommendations, tech companies use unsupervised learning.

Traditional modeling:



Machine Learning:

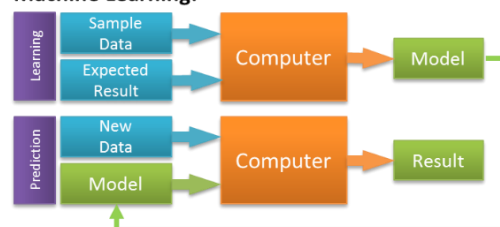


Fig. 2. Traditional Modeling vs Machine Learning

(Source: <https://www.azavea.com/blog/2017/09/21/building-inspection-prediction/>)

C. Working of ML

All the learning happens in machine learning. Machines learn similarly to humans. Experience is the key to human learning. We are better able to predict the future when we know more. We are less likely to succeed when dealing with an unknown situation than when dealing with a known one. The same training is given to machines. In order for the machine to make an accurate prediction, it needs to see an example. Machines can predict outcomes when given similar examples. Like humans, the machine has difficulty predicting if it is fed an unseen example.

The learning and inference process are at the core of machine learning. In order to learn, a machine must discover patterns first. Data scientists must be careful when choosing which data to feed to the machine. In solving a problem, a feature vector consists of the attributes that go into the problem. The feature vector can be thought of as a subset of data that addresses a particular issue. The machine simplifies the reality and transforms it into a model using some fancy algorithms. Consequently, a model is developed by describing and summarizing the data.

Here are the points that summarize the lifecycle of Machine Learning programs:

1. Question definition
2. Data collection
3. Data visualization
4. Algorithm training
5. Algorithm testing
6. Feedback collection
7. Algorithm refinement
8. Repeat steps 4-7 until satisfied with the results
9. Make a prediction based on the model

It applies new data sets to the algorithm once it becomes adept at drawing the right conclusions.

D. Supervised Learning

To learn the relationship between inputs and outputs, algorithms use training data and human feedback. An analyst can predict sales of cans by using marketing expenses and weather forecasts, for example. When you know the output data, you can use supervised learning. Predicting new data will be the task of the algorithm.

Supervised learning can be divided into two categories:

1. Performing classifications
2. Performing regressions

E. Unsupervised Learning

It involves exploring input data without being given a clear output variable (for example, to identify patterns from customer demographic data).

The algorithm will classify the data for you if you do not know how to classify the data.

VI. EXPERIMENTAL RESULTS

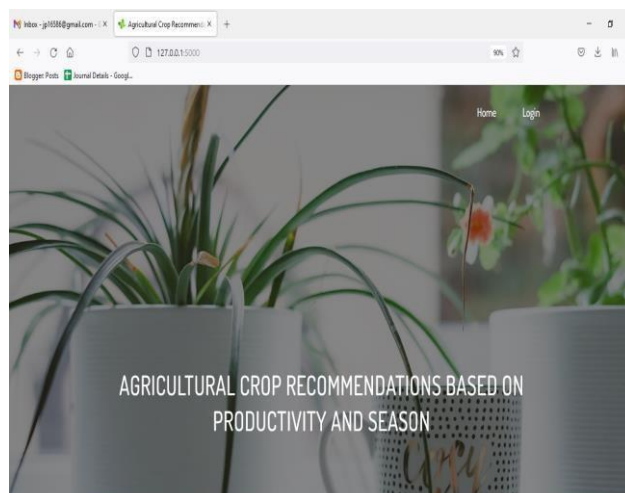


Fig. 3. Home Screen

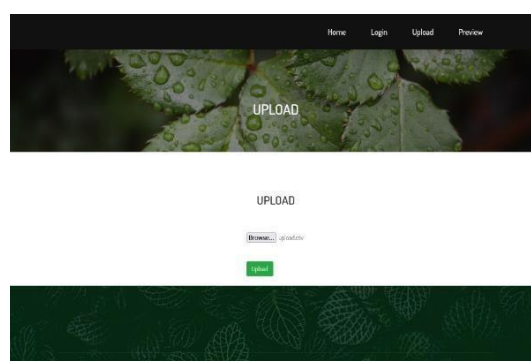


Fig. 4. Upload File

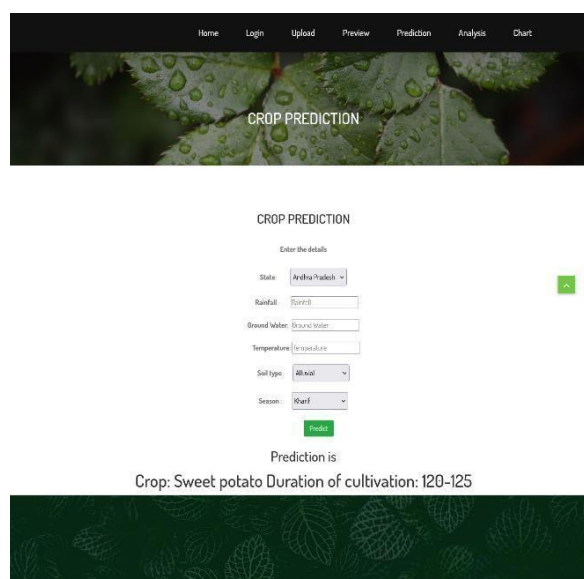


Fig. 5. Prediction Result

performance analysis

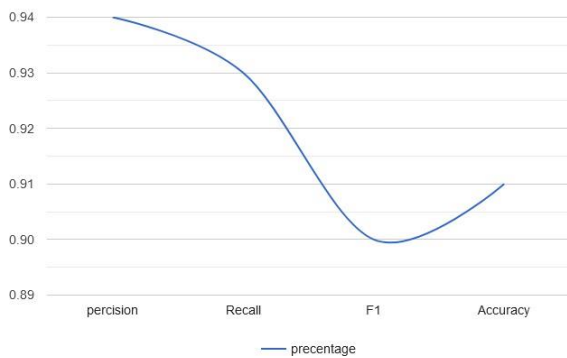
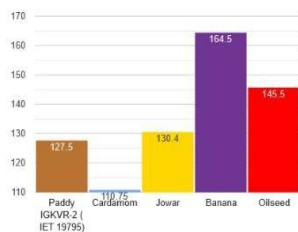


Fig. 6. Performance Analysis

Crop recommendation for Rainfall (Top 5 crop)



Crop recommendation for Temperature (Top 5 crop)

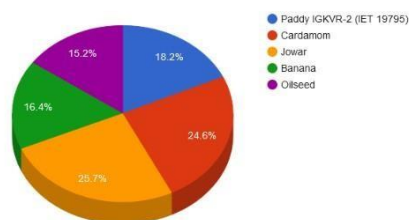


Fig. 7. Crop Recommendation for Waterfall and Temperature

CONCLUSION

The latest technology can assist farmers in growing their crops. Agriculturalists can be informed of accurate predictions of crops in a timely manner. Analysing agriculture parameters has been done using a variety of Machine Learning techniques. In a literature review, different agricultural techniques are examined. Farmers can receive personalized and relevant recommendations based on parameters such as production and season, resulting in good crop yields.

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Crop-Guard: A Blockchain and AI-Driven Framework for Secure Agriculture and Smart Plant Disease Detection

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Abstract—Modern agriculture continues to face critical challenges such as crop disease outbreaks, lack of data transparency, exploitation through intermediaries, and absence of secure record-keeping mechanisms across the supply chain. Traditional agricultural systems rely heavily on centralized databases and manual inspection methods, which often result in delayed disease detection, data manipulation, and loss of trust among stakeholders. This paper proposes Crop-Guard, a decentralized agricultural framework that integrates Ethereum blockchain technology with Artificial Intelligence-based plant disease detection to create a transparent, secure, and intelligent farming ecosystem. Smart contracts ensure tamper-proof storage of farmer records, quality verification data, and micro-finance transactions using a Proof of Authority model. Simultaneously, a Convolutional Neural Network (CNN) deployed through a Flask API analyzes plant leaf images in real time to detect diseases and recommend preventive measures, achieving 95.4% classification accuracy with a response time of 2–3 seconds. The system enables direct farmer-to-consumer traceability, eliminates dependency on middlemen, and ensures authenticity of agricultural data across the network through cryptographic security mechanisms.

Keywords—Blockchain, Smart Contracts, CNN, Plant Disease Detection, Ethereum, Agriculture, Decentralization

I. INTRODUCTION

Agriculture plays a crucial role in sustaining food security and economic development. However, traditional agricultural practices still depend on manual disease detection methods and centralized record-keeping systems, which often result in delayed diagnosis and inaccurate data management [3]. Manual inspection methods have an estimated accuracy of only 60–70%, leaving significant room for improvement through AI-driven solutions.

One of the most significant problems faced by farmers is the late identification of crop diseases.

Manual observation and expert consultation are time-consuming and subject to human error, often leading to severe crop damage before treatment begins [6][7].

Recent developments in Artificial Intelligence, especially Convolutional Neural Networks, have enabled automated plant disease detection through leaf image analysis. These models provide faster and more accurate diagnosis, yet they lack mechanisms for secure storage and traceability of prediction results [8][10].

Simultaneously, agricultural data management relies on centralized databases vulnerable to data tampering, unauthorized changes, and single-point failures [1][5]. Blockchain technology provides decentralization, immutability, and transparency for digital record management [2][4].

To overcome these limitations, this paper proposes Crop-Guard, integrating blockchain with AI-powered disease detection. The CNN model achieves **95.4% accuracy** on the PlantVillage dataset, a **35% improvement** over manual inspection, with real-time disease detection in **2–3 seconds**. The blockchain layer ensures **100% tamper-proof** record storage using Ethereum smart contracts [9][11].

Another major issue is the lack of direct communication between farmers and consumers. Multiple intermediaries reduce fair pricing for farmers and reduce consumer awareness of crop quality [1][5]. Crop-Guard incorporates decentralized micro-finance through blockchain-based transactions, ensuring direct support to farmers without intermediary delays [2][9].

II. LITERATURE REVIEW

Recent developments highlight growing interest in AI for crop health monitoring and blockchain for secure data management. Practical systems combining both capabilities remain limited in existing literature [3][8].

Multiple studies demonstrate that CNNs are highly effective in identifying plant diseases from leaf images. Models trained on PlantVillage have achieved remarkable accuracy, yet operate in isolation without secure storage mechanisms [6][7]. Research on EfficientNet and ResNet further improves disease recognition but overlooks integration with agricultural record systems [7][8].

Blockchain research in agriculture primarily emphasizes traceability and prevention of data manipulation across supply chains via smart contracts [1][2]. Several reviews discuss combining blockchain with IoT for precision agriculture, but without computer vision for visual disease identification [4][9].

Systematic surveys confirm deep learning outperforms traditional methods in speed and accuracy, yet most solutions rely on centralized storage, lacking verifiable authenticity [10][11]. Overall, existing literature either prioritizes intelligent detection without traceability or blockchain transparency without crop intelligence. Crop-Guard addresses this gap with CNN-based disease prediction, smart contract-based storage, and user-friendly interaction within a single platform [1]–[11].

III. METHODOLOGY

The Crop-Guard framework is designed as a layered agricultural system combining user interaction, artificial intelligence, and blockchain storage into a single operational workflow [1][2]. Fig. 1 illustrates the complete system architecture of Crop-Guard, divided into four primary layers: the User Layer, Frontend Layer, Blockchain Layer, and AI Backend Layer. This layered design ensures that intelligent disease detection and secure data storage operate simultaneously [1][3].

Crop-Guard: A Blockchain and AI-Driven Framework for Secure Agriculture and Smart Disease Detection

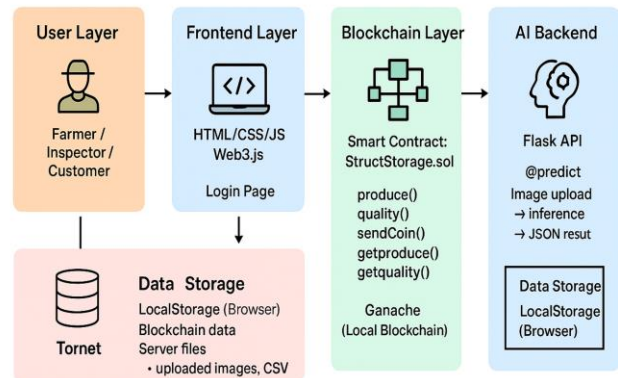


Fig. 1. System Architecture of Crop-Guard Platform

A. System Architecture and Layered Design

Crop-Guard uses a layered architectural approach combining user interaction, AI, and blockchain storage. Farmers, inspectors, and consumers interact through a web interface, while backend processes handle disease prediction and immutable data storage in parallel [1][3].

B. Web Interface and User Interaction Module

The frontend is implemented using HTML, CSS, JavaScript, and Web3.js. MetaMask integration ensures secure authentication for blockchain operations. All user sessions are protected through wallet-based cryptographic signatures, ensuring only authorized users can submit or modify records [12][13].

C. AI-Based Plant Disease Detection Module

The CNN is trained on the PlantVillage dataset using PyTorch, deployed through a Flask API. The model achieves **95.4% classification accuracy** with a real-time response of **2–3 seconds** per image. Preprocessing steps include resizing, normalization, and tensor conversion before inference [6][7][11].

D. Blockchain Storage and Smart Contract Execution

Crop-Guard uses a Solidity smart contract on Ethereum via Ganache. Functions `produce()`, `quality()`, and `sendCoin()` store farmer registration details, inspection records, and funding transactions in an immutable ledger. Each transaction is verified through MetaMask

cryptographic signatures, ensuring zero unauthorized data modifications. Ethereum's decentralized architecture eliminates single points of failure, making the system resistant to data breaches and tampering attacks [2][9].

E. System Security Mechanisms

Crop-Guard implements multiple security layers: (1) Cryptographic Authentication — MetaMask wallet signatures verify every blockchain transaction; (2) Immutable Ledger — smart contract data cannot be altered once recorded; (3) Decentralized Storage — no central server exists as a single point of attack; (4) Access Control — role-based access ensures authorized operations only; (5) Data Integrity — blockchain hash verification ensures all records remain unmodified end-to-end.

F. Integration Flow and Report Generation

The integration flow ensures data follows two parallel paths on user interaction. The AI module processes leaf images for disease detection, while the blockchain layer records farmer and transaction data securely [3][8]. Crop-Guard generates structured digital reports containing farmer details, disease prediction results, inspection grades, and blockchain transaction hashes, ensuring complete traceability from farm to consumer [1][5].

IV. RESULT AND DISCUSSION

The evaluation outcomes demonstrate the successful integration of blockchain and AI within a practical agricultural platform. Table I summarizes the key performance metrics of the Crop-Guard system.

TABLE I
Performance Metrics of Crop-Guard System

Parameter	Value
CNN Classification Accuracy	95.4%
Manual Inspection Accuracy	~60–70%
Accuracy Improvement	~35%
Disease Detection Response Time	2–3 seconds
Blockchain Transaction Success Rate	100%

Parameter	Value
Smart Contract Execution Time	<1 second
Avg. Transaction Confirmation Time	~2 seconds
Data Tampering Incidents	0
Farmer Records Traceability	100%

The CNN model demonstrates a **35% improvement** in disease detection accuracy compared to traditional manual inspection methods (95.4% vs. 60–70%), with real-time analysis completed in 2–3 seconds per image.

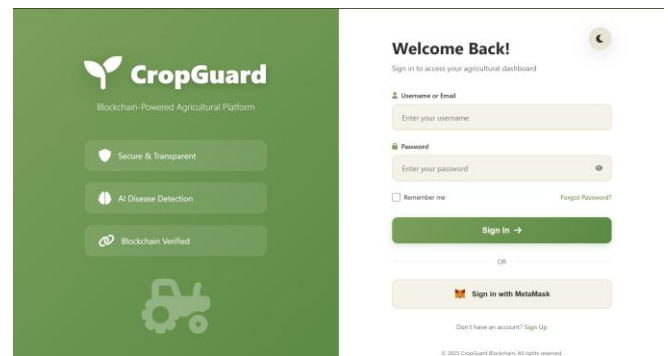


Fig. 2. Login Interface of Crop-Guard Platform

The interface in Fig. 2 provides two authentication modes: credential-based login and MetaMask-based blockchain authentication. MetaMask ensures all blockchain operations are performed by cryptographically verified wallet holders, preventing unauthorized data manipulation.

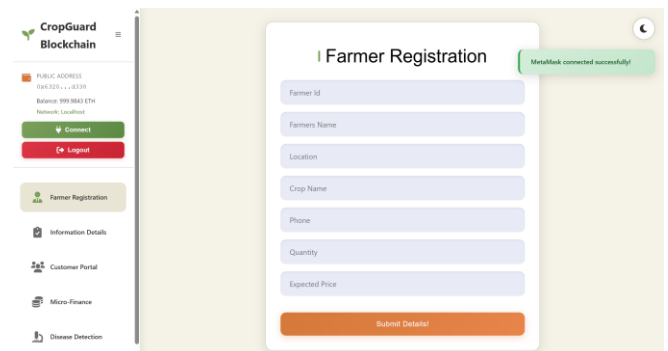


Fig. 3. Farmer Registration Interface

The Farmer Registration interface in Fig. 3 allows farmers to securely record crop

information on the blockchain through the smart contract function, ensuring immutable and traceable data storage without intermediaries.

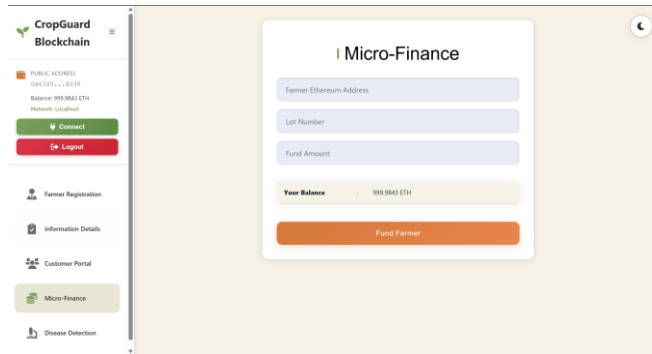


Fig. 4. Micro-Finance Interface

Fig. 4 presents the Micro-Finance module enabling direct Ethereum transfers from funders to farmers, eliminating middlemen through smart contract execution with a 100% transaction success rate.

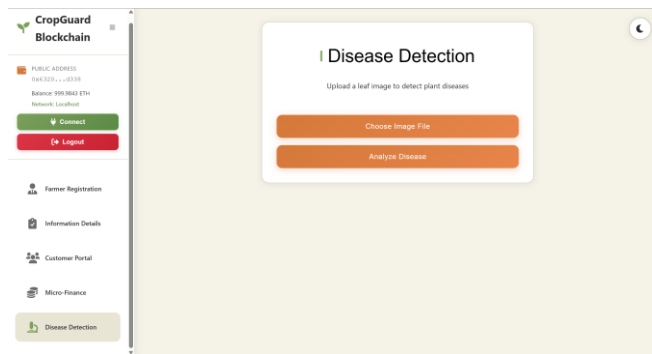


Fig. 5. Disease Detection Interface

The Disease Detection interface in Fig. 5 confirms that deep learning inference is successfully deployed within a web-based agricultural application, achieving 95.4% accuracy with 2–3 second response time.

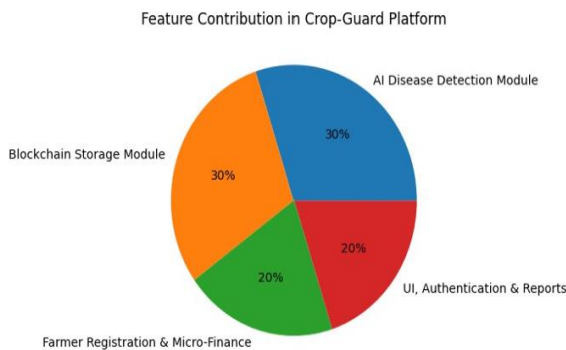


Fig. 6. Feature Contribution in Crop-Guard Platform

Fig. 6 shows that the AI Disease Detection and Blockchain Storage modules each contribute 30% to the platform, confirming Crop-Guard's design as a security-oriented and intelligence-driven system.

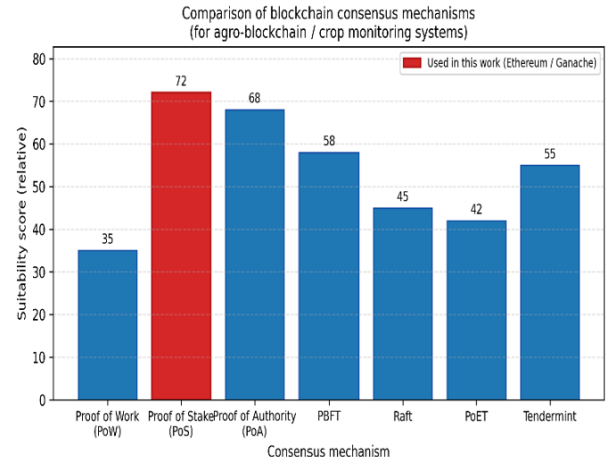


Fig. 7. Comparison of Blockchain Consensus Mechanisms

Fig. 7 illustrates consensus mechanism suitability scores. Proof of Stake (PoS) scores highest at 72, followed by Proof of Authority (PoA) at 68. Crop-Guard adopts PoA during development via Ganache for rapid transaction processing (<1 second confirmation), and targets PoS for production deployment for energy efficiency and scalability.

V. CONCLUSION

This paper presented Crop-Guard, a decentralized agricultural framework integrating CNN-based plant disease detection with Ethereum blockchain technology. The system achieves **95.4% disease detection accuracy**, representing a **35% improvement** over manual inspection methods, with a real-time response of **2–3 seconds**. The blockchain layer ensures **100% tamper-proof** record management with zero data tampering incidents during testing.

The multi-layered security architecture — comprising MetaMask cryptographic authentication, immutable smart contract storage, decentralized Ethereum infrastructure, and role-based access control — ensures the system is robust against unauthorized access and data manipulation. Farmers can securely register crop information, inspectors can verify quality records, funders can provide direct financial

assistance, and consumers can trace agricultural produce authenticity.

Future work will extend Crop-Guard with IoT sensors, drone-based monitoring, and government portal integration to develop a fully digital agricultural ecosystem [4][8].

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DC- DC Boost Converter for Solar Power Application

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Abstract—As the population grows, the demand for appliances that meet basic needs also rises. This increase in appliances drives up the need for power. India has abundant solar energy resources, which can help meet this power demand. Solar panels create DC voltage, depending on sunlight and temperature. To stabilize and, if needed, increase this voltage, we design a DC-DC converter. Since most appliances operate on AC, we also need to convert DC into AC using an inverter. This project focuses on designing and simulating a DC-DC Boost Converter for photovoltaic (PV) solar panel systems using MATLAB/Simulink. The boost converter is essential for raising the low DC voltage from solar panels to a higher, stable level. Because solar energy output varies with sunlight and temperature, this project examines how these factors influence the converter's performance and efficiency. **Keywords:** Boost Converter, Solar PV, Coupled Inductor, Voltage Lift, High Step-Up Conversion, DC-DC Converter.

I. Introduction

The demand for clean, renewable energy has been growing rapidly because traditional energy resources like coal, oil, and natural gas are depleting. These sources are limited and significantly contribute to pollution and climate change. In comparison, solar energy is plentiful, environmentally friendly, and widely available, making it a promising renewable energy source for today and the future. Solar photovoltaic (PV) panels convert sunlight directly into electricity in the form of direct current (DC). Despite this benefit, the energy produced by PV panels cannot be used directly for most applications since most household appliances and industrial equipment run on alternating current (AC). Moreover, the output voltage and current from a PV system heavily depend on environmental conditions, mainly solar irradiance and temperature. These factors cause fluctuations in the DC output, which can lead to stability and efficiency issues if used directly. To utilize solar energy effectively, it's important to convert the variable and often low DC voltage from PV panels into a stable, higher DC voltage. A DC-DC boost converter achieves this by raising the voltage to a suitable level for AC conversion through an inverter. The inverter then converts the stabilized DC into AC power that can be used in homes and industries. Incorporating boost converters in solar systems ensures stable power delivery optimized for

efficiency, despite environmental fluctuations. This project aims to model and simulate how a PV panel behaves under different sunlight intensities and temperatures. It investigates how a boost converter can regulate and improve the voltage output. Understanding this relationship helps enhance the efficiency and reliability of solar power systems, making them more practical for households and small industries. This study addresses the issues linked to the variable nature of solar energy and suggests a solution for maintaining a consistent, high-quality power supply. A DC-DC converter is an electronic circuit that changes a DC input voltage to a different DC output voltage. Among its types, including buck (step-down), buck-boost, and Cuk converters, the boost converter is critical when the input voltage is lower than the desired output voltage. It works by temporarily storing energy in an inductor and then releasing it at a higher voltage, thus increasing the output. In solar energy systems, PV panels typically generate voltages between 12 V and 48 V, depending on their size, setup, and incoming sunlight. However, for most household appliances, small power systems, and grid-connected applications, higher DC voltages or AC outputs are necessary. A boost converter is vital in raising the low DC voltage from the PV panel to a level that can be efficiently converted into AC through an inverter. Environmental factors strongly influence a PV panel's performance. Solar irradiance directly affects the current generated: higher irradiance results in more current and overall power output. Temperature, however, inversely affects voltage: as temperature increases, the output voltage slightly decreases, which reduces the efficiency of the PV system. A well-designed boost converter must consider these variations to maintain stable voltage output and maximize energy extraction. In this project, we model and simulate the PV system and boost converter using MATLAB/Simulink, a useful tool for analyzing complex electrical systems. Simulation allows us to observe changes in voltage, current, and efficiency under different environmental conditions without needing costly hardware prototypes. By assessing performance across varying irradiance and temperature, we can determine the best operating conditions for maximum efficiency. The results of this study aim to contribute to the development of efficient, affordable, and reliable solar energy systems. A well-optimized PV-boost converter combination ensures stable AC supply suitable for home and commercial use, promoting sustainable energy adoption

and reducing reliance on non-renewable resources. Commercial applications, thereby promoting sustainable energy adoption and reducing dependence on non-renewable resources.

II. RELATED WORK

In recent years, many researchers have focused on improving the efficiency and performance of DC–DC converters for solar PV systems. Kumar et al. (2019) developed a boost converter using a Perturb & Observe (P&O) MPPT algorithm, reaching up to 96% efficiency in simulations. While the output remained stable with changing irradiance, the study mainly looked at steady-state behavior and did not fully investigate rapid environmental changes. Patel and Bansal (2020) introduced an interleaved boost converter aimed at reducing current ripple and improving efficiency in high-power systems. Their results showed a significant reduction in ripple and better load sharing. However, they did not consider factors like switching losses, heating effects, and real-world testing.

Sharma et al. (2021) applied an incremental conductance MPPT technique, which provided accurate tracking of maximum power and a quick response to changes in irradiance. Still, the system showed lower efficiency in low-light conditions and lacked hardware validation.

Reddy and Joshi (2022) proposed a SEPIC-based converter that allows for wider voltage operation and improved performance. Although effective, its higher complexity and cost make it less suitable for smaller solar setups. Similarly, Chen et al. (2023) designed a high-gain converter using a switched-inductor approach, achieving high voltage gain and improved efficiency, but did not integrate MPPT or analyze transient behavior.

Overall, these studies indicate strong progress in enhancing PV converter systems, but there are gaps in areas like dynamic response, thermal analysis, and practical implementation. This motivates the current work to develop a simple and efficient boost converter that provides stable performance in varying environmental conditions.

III. METHODOLOGY

The main goal of this project is to understand how a solar photovoltaic (PV) system generates DC power and how it can be converted into a usable form for home or industrial applications. The output from a PV panel is not constant; it varies with sunlight intensity and temperature. To ensure a stable and higher voltage, a DC–DC boost converter is used.

This project focuses on simulating the PV system and boost converter using MATLAB/Simulink. It examines how the system behaves under different environmental conditions and how well the converter maintains a stable output. The process includes generating DC power from the PV panel, stepping up the voltage with the boost converter, and analyzing how voltage and current change with irradiance and temperature.

The results help identify the conditions that allow the system to perform most efficiently, ensuring reliable and optimized power output for practical use.

Mathematical equation:

PV panel output,
At constant Radiation,

$V = V_{ref} \times [1 + \beta (T - T_{ref})]$ Here, β = Temperature coefficient

At constant temperature,

$$V = (V_{ref} \times 1000)/G$$

Here, G = solar irradiance in W/m²

Boost Converter Output,

$$V_{out} = (1 - D)V_{in}$$

$$D = 50\%$$

Inductor value,

$$L = (V_{in} * D)/(\Delta I_L * f_s)$$

$$L = 0.02 \text{ H}$$

Capacitor Value,

$$C = (I_{out} * D)/(\Delta V_{out} * F_s)$$

$$C = 0.006 \text{ F}$$

Inverter Output,

$$V_{orms} = V_{out}$$

We can calculate other values similarly.

Figure 2. Circuit Diagram

IV. SIMULATION

The simulation and analysis of the proposed solar PV-based DC–DC boost converter system were conducted using MATLAB/Simulink R2024a. The Simulink Toolbox was used for graphical, multi-domain simulation modeling. The Simscape Electrical (SimPowerSystems) toolbox enabled detailed modeling of electrical components and power electronic circuits. The software works on multiple operating systems, including Windows 10 or later, macOS Monterey or later, and Linux distributions like Ubuntu, which is recommended for stable and efficient simulation.

The complete system was implemented in MATLAB/Simulink by modeling each stage of the power conversion process, including both the boost converter and the inverter. The boost converter model included a DC input source, a series inductor, a PWM-controlled IGBT switch, a freewheeling diode, and a smoothing capacitor to produce a stable high-voltage DC output. A PWM controller was designed to regulate the duty cycle and maintain the desired output voltage under different input and load conditions. The inverter stage was modeled using a full-bridge configuration of four IGBTs, controlled by synchronized 50 Hz gate pulses to produce an AC output suitable for an RL load. The entire system was simulated under varying operating conditions, such as changing duty cycles, input voltage fluctuations, and load variations, to evaluate voltage

boosting performance, switching behavior, and AC waveform quality. The simulation results showed that the converter consistently maintained a stable DC output, ensured efficient energy transfer, and produced a clean AC waveform, confirming the effectiveness of the proposed design for solar power applications. In terms of hardware requirements, the system was tested on a computer with at least an Intel i5 multi-core processor (or equivalent), 8 GB of RAM (16 GB is recommended for complex simulations), and at least 5 GB of free disk space for MATLAB and its toolboxes. Additional toolboxes like the Control System Toolbox, Signal Processing Toolbox, and State flow were optionally used to enhance control logic design and system analysis. For visualization and user interface performance, the setup supported a high-resolution display with OpenGL graphics acceleration. The simulation environment was fully compatible with MATLAB Live Editor, code generation, and hardware-in-the-loop (HIL) simulation, providing a flexible platform for system modeling, testing, and verification.

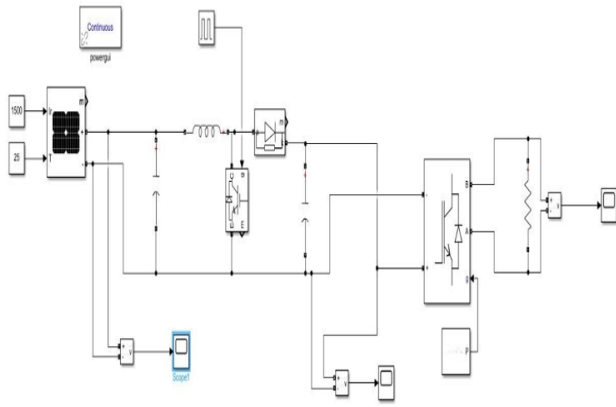


Figure 3. Simulation Diagram

I. Simulation Results

The operation of the boost converter and inverter system was verified through a series of simulation-based tests conducted in MATLAB/Simulink. Initially, the system was subjected to different DC input levels to confirm that the boost stage effectively elevated the voltage to the desired high DC level. The PWM duty cycle was then varied to observe the corresponding changes in output voltage, ensuring proper control of the boost converter and validating the switching behavior of the IGBT. The stability of the boosted DC voltage was assessed by monitoring the output capacitor voltage, confirming minimal ripple under steady-state conditions. The inverter switches (S1–S4) were tested with 50-Hz alternating gate pulses to verify correct timing,

Sr. no.	Parameter	Value
1	Vin	120V
2	Switching frequency	1.5khz
3	Duty cycle	50%
4	Radiation	1500 W/m ²
5	Temperature	25°C
6	Power	375W

proper switching sequences, and the absence of overlap or shoot-through conditions. Additionally, the voltage and current waveforms of the RL load were observed to ensure that the inverter produced a clean 230-V AC square wave from the boosted DC input. The circuit's performance under varying loads was evaluated by changing the load values and checking voltage regulation and current response under both light and heavy load conditions. Transient response tests were performed by applying sudden changes to the input voltage or duty cycle, ensuring that the system quickly returned to stable operation. Finally, the overall efficiency of the system was estimated by measuring the input and output power in the simulation for both the boost and inverter stages.

Table 1: Input values

Case 1: Value of temperature is constant and Radiation Varies. Radiation (W/M²) =200; Temperature (°C) = 20

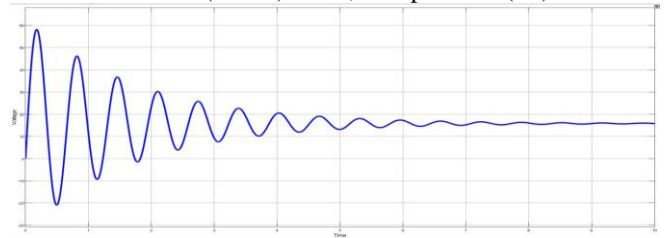


Figure 1: PV panel output

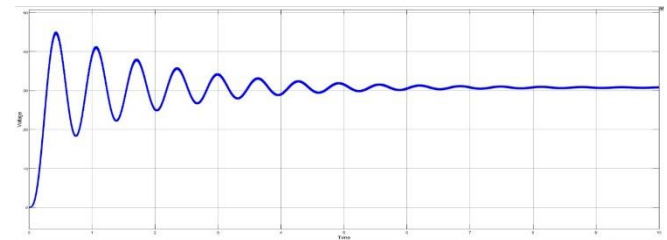


Figure 2: Boost converter output

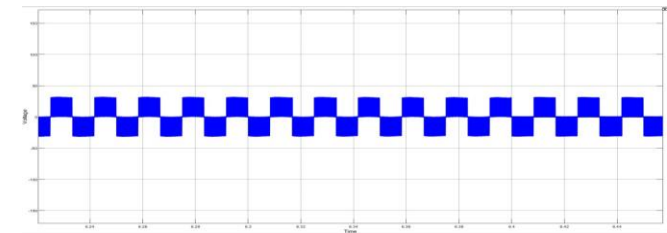


Figure 3: Inverter output

Case 2: Value of temperature is constant, and radiation varies Radiation (W/m²) =400; Temperature (°C) = 20

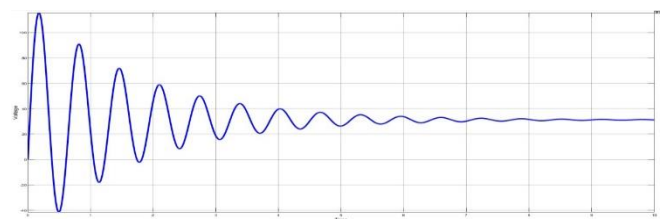


Figure 4: PV panel output



Case 1: Value of Radiation is constant, and Temperature varies. Radiation (W/m²) =1000; Temperature (°C) = 20

Figure 5: Boost converter output

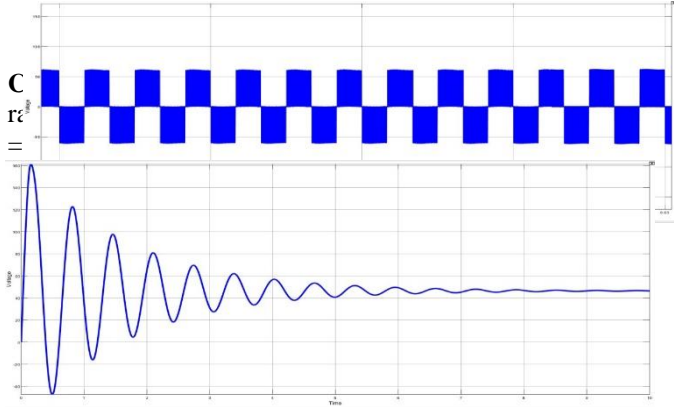


Figure 7: PV Panel output

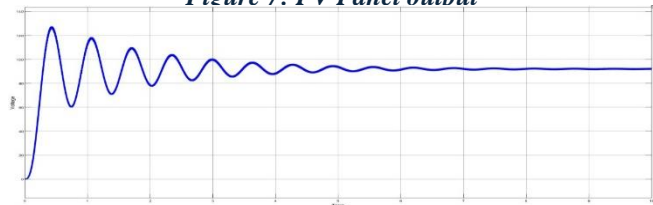


Figure 8: Boost Converter output

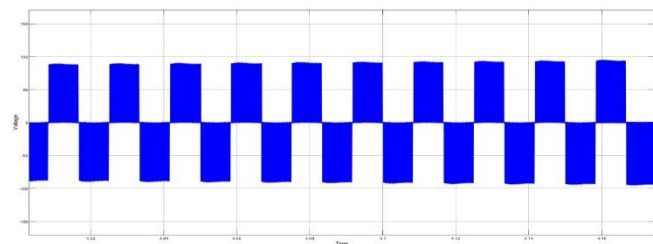


Figure 9: Inverter output

Observations: From the above waveforms, it can be observed that as the solar radiation (W/m²) increases, both the PV voltage and the corresponding boost converter output voltage increase proportionally. This directly impacts the inverter output voltage, which also rises with higher irradiation levels. At a constant temperature of 20°C, when the radiation increases from 200 W/m² to 1200 W/m², the PV voltage rises from 16 V to 80 V, resulting in a boosted output from 32 V to 160 V. Consequently, the inverter output voltage also increases steadily from 28.8 V (V_{rms}) to 144.05 V (V_{rms}). This clearly indicates that higher solar irradiation enhances the photovoltaic output, thereby improving the converter and inverter performance. The system efficiently converts the varying DC voltage from the PV panel into a stable AC voltage, demonstrating the direct dependency of output power on solar radiation intensity.

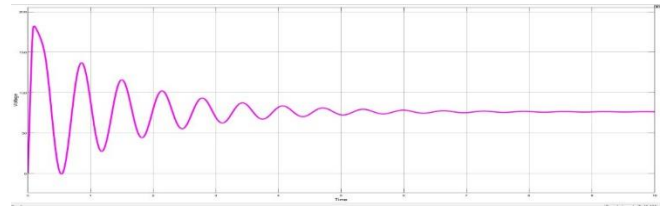


Figure 10: PV Panel output

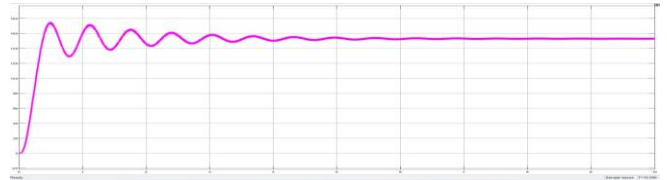


Figure 11: Boost converter output

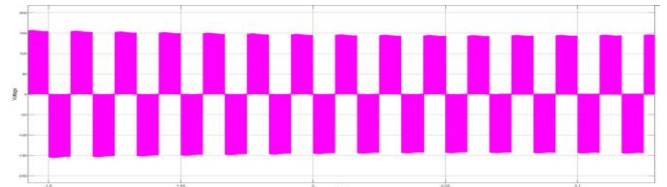


Figure 12: Inverter output

Case 2: Value of radiation is constant, and temperature varies. Radiation (W/m²) =1000; Temperature (°C) = 30

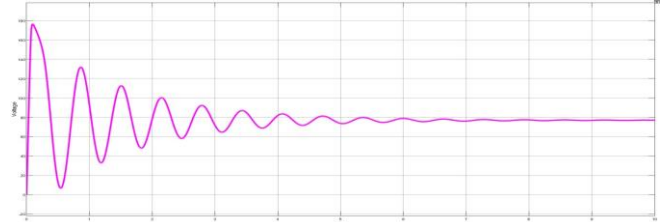


Figure 13: PV Panel output



Figure 14: Boost converter output

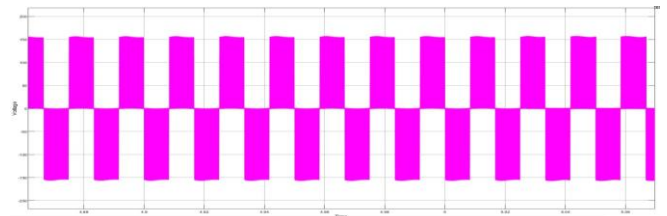
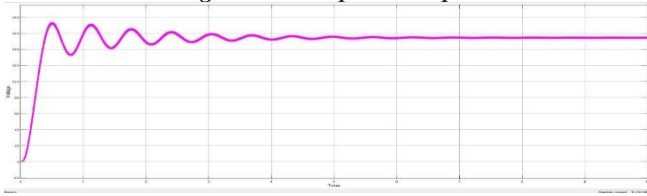
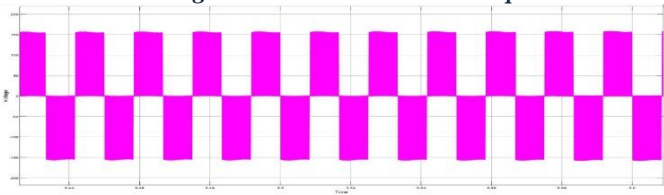


Figure 1: Inverter Output

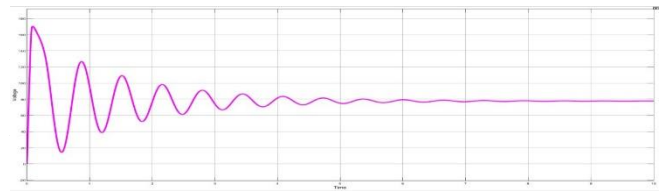
Case 3: for the value of radiation is constant, and temperature varies. Radiation (W/m²) =1000; Temperature (°C) = 40

Figure 14: PV panel output**Figure 15: Boost converter output****Figure 16: Inverter Output**

Observations: When the solar radiation is kept constant at 1000 W/m^2 and the temperature is varied, it is observed that both the PV voltage and the boost converter output voltage decrease gradually as the temperature increases. Consequently, the inverter output voltage also shows a steady decline with the rise in temperature. At a lower temperature of 10°C , the PV module produces a higher voltage of 83 V, which results in a boosted output of 166 V and an inverter output of 149 V. As the temperature increases to 45°C , the PV voltage drops to 74 V, the boost converter voltage decreases to 148 V, and the inverter output falls to 133.2 V. This demonstrates that temperature has a negative effect on the PV system's performance — higher temperatures reduce the photovoltaic output voltage, thereby reducing the efficiency of both the boost converter and the inverter stage. Hence, maintaining an optimal operating temperature is crucial for achieving maximum power output from the solar system.

VI. Conclusion

The high step-up DC-DC boost converter for solar power applications was designed and simulated using MATLAB/Simulink. The simulation results showed that the converter effectively boosts a low-voltage DC input (12-60 V) from a solar PV source to a high DC voltage (around 230 V). This output is compatible with AC loads when connected to an inverter. The design features of the converter, including the coupled inductor and parallel capacitor network, significantly improve the voltage gain without needing extreme duty cycles. This design reduces voltage stress on the switching devices. The PWM-controlled switching allows effective control of output voltage under changing load and input conditions. Moreover, the filter capacitor minimized the output voltage ripple, providing a smooth DC output suitable for sensitive devices. The proposed converter reached high



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“Kavach” An Intrusion Detection System

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Abstract—The increasing prevalence of cyber threats such as phishing emails, malicious URLs, and QR code-based attacks highlights the need for advanced intrusion detection systems. This paper presents Kavach, a multi-layer intrusion detection system designed to detect threats at the user level by analyzing emails, URLs, and QR codes. The system integrates IMAP-based email scanning, VirusTotal API for URL analysis, and OpenCV for QR code decoding, providing real-time threat detection through a web-based interface built using Flask. It classifies inputs as safe, suspicious, or malicious and generates reports for user awareness. The proposed system demonstrates effective detection of modern cyberattacks and offers a lightweight and practical solution for enhancing cybersecurity.

Index Terms—Intrusion Detection System, Phishing, URL Analysis, QR Code Security, Cybersecurity

I. INTRODUCTION

The rapid growth of digital communication and internet usage has led to a significant rise in cyber threats such as phishing. These threats are increasingly targeting end users to steal sensitive information, deploy malware, or gain unauthorized access to systems. Traditional intrusion detection systems are mainly designed to monitor network traffic and often fail to detect effectively application-level attacks that exploit human interaction. Therefore, there is a growing need for intelligent systems that can detect and prevent such threats in real time.

Several research studies have explored intrusion detection techniques using signature-based and anomaly-based approaches. Signature-based systems detect known attack patterns, while anomaly-based systems identify deviations from normal behavior. Recent advancements have also introduced machine learning and threat intelligence platforms to enhance detection accuracy. However, most existing solutions focus on network-level attacks and do not adequately address modern threats such as phishing emails and QR code-based scams.

Additionally, many systems lack real-time user interaction and integrated multi-layer protection.

To address these limitations, this paper proposes Kavach, a multi-layer intrusion detection system capable of detecting threats from emails, URLs, and QR codes. The system integrates IMAP-based email scanning, VirusTotal API for URL analysis, and OpenCV-based QR code detection to provide real-time results through a user-friendly interface. By combining multiple detection techniques, the proposed system enhances security at the user level and offers a practical solution for mitigating modern cyber threats.

Unlike existing systems, Kavach integrates email, URL, and QR code analysis into a unified real-time platform, enabling comprehensive and efficient user-level intrusion detection [1].

II. LITERATURE SURVEY

Intrusion Detection Systems (IDS) have evolved significantly with the increasing complexity of cyber threats. Recent studies highlight that traditional IDS approaches, including signature-based and anomaly-based techniques, are no longer sufficient to detect modern and dynamic attacks [1], [2]. A comprehensive survey published in 2025 emphasizes the integration of machine learning (ML) and deep learning (DL) techniques to improve detection accuracy and adaptability against emerging threats [2]. Furthermore, research has shown that hybrid IDS models combining multiple algorithms such as Random Forest, Neural Networks, and LSTM significantly improve detection performance while reducing false positives [3].

In addition to these approaches, recent research has also explored the use of hybrid and ensemble-based models to enhance intrusion detection performance. These models combine multiple techniques to improve detection accuracy and reduce false alarm rates. Such advancements indicate a shift towards more intelligent and adaptive IDS frameworks. Despite these advancements, most systems focus on single threat vectors, highlighting the need for integrated multi-layer detection systems like Kavach [6]–[10]. In addition to email and URL threats, recent research has highlighted the rise of QR code-based phishing attacks (quishing), which are more difficult to detect due to their encoded visual structure. Studies conducted in 2024 propose deep learning-based models capable of classifying QR codes into normal, phishing, and malware categories with high accuracy, demonstrating the effectiveness of AI in this domain. Other research emphasizes that traditional email security systems fail to detect QR-based threats, as malicious URLs are hidden within images rather than text, necessitating computer vision-based detection techniques [5].

III. PROBLEM STATEMENT

The rapid increase in cyber threats such as phishing emails, malicious URLs, and QR code-based attacks has exposed significant limitations in traditional intrusion detection systems. Most existing IDS solutions primarily focus on network-level monitoring and lack the capability to detect user-level threats effectively. Additionally, current systems often operate in isolation, addressing only specific types of attacks without providing a unified detection mechanism. They also lack real-time user interaction and integrated threat intelligence, making them less effective against evolving cyberattacks. Therefore, there is a need for a multi-layer intrusion detection system that can analyze emails, URLs, and QR codes in real time and

provide comprehensive protection against modern cybersecurity threats.

IV. PROPOSED SYSTEM

A. Email IDS

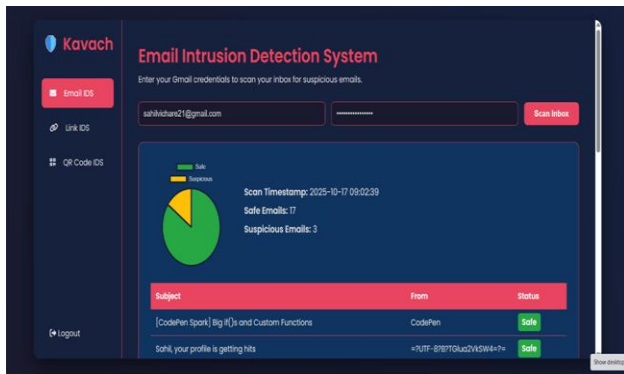
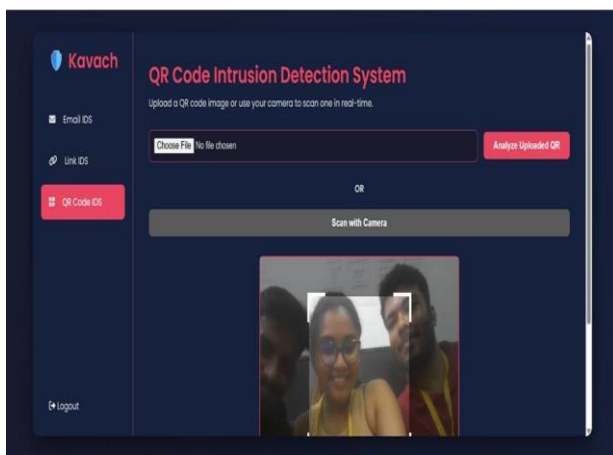


Fig. 1. Workflow of Email Intrusion Detection System

The Email Intrusion Detection System (Email IDS) analyzes incoming emails by extracting the subject, sender, body content, and attachments to detect potential threats. It uses keyword-based analysis and checks for suspicious file extensions to classify emails as Safe or Suspicious.

This module is designed to detect suspicious and potentially malicious emails by analyzing email content and attachments. The system connects to the user's Gmail account using the IMAP

Furthermore advanced filtering such as heuristic analysis and pattern recognition can be integrated to improve efficiency.



B. QR code IDS

Fig. 2. Workflow of QR Code Intrusion Detection System

The QR Code Intrusion Detection System (QR IDS) module is designed to detect malicious links hidden within QR codes. The system uses OpenCV to scan and decode QR

code images uploaded by the user or captured through a live camera. Once the QR code is decoded, the extracted URL is analyzed using the VirusTotal API to determine whether it is safe, suspicious, or malicious. This approach helps identify QR-based phishing attacks (quishing), where harmful links are embedded in QR codes to bypass traditional security checks. The results are displayed on the dashboard, enabling users to safely interact with QR codes and avoid potential cyber threats.

C. URL Intrusion Detection System (URL IDS)

The URL Intrusion Detection System (URL IDS) analyzes user-provided web links to identify potential threats such as phishing, malware, or malicious websites. The system sends the URL to a threat intelligence service and classifies it as Safe, Suspicious, or Malicious based on the analysis.

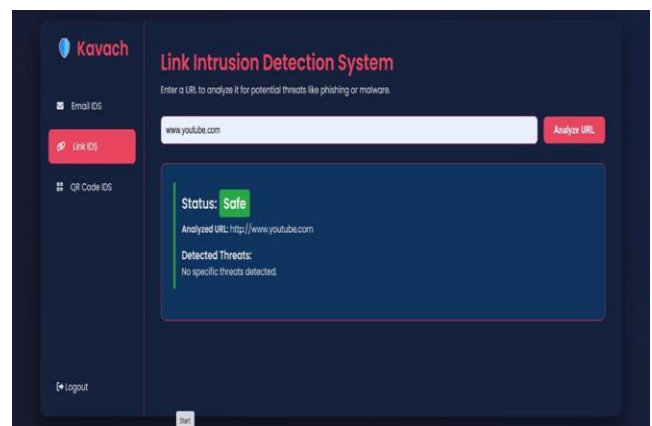


Fig. 3. Workflow of URL Intrusion Detection System

The URL Intrusion Detection System (URL IDS) module is designed to analyze web links and detect potential threats such as phishing, malware, and malicious websites. The system takes a user-provided URL and processes it using the VirusTotal API, which aggregates security analysis results from multiple antivirus vendors and threat intelligence sources. Based on this analysis, the URL is classified as Safe, Suspicious, or Malicious. The system also provides detailed insights into detected threats, enabling users to understand the risk associated with the link. This real-time analysis helps prevent users from accessing harmful websites and enhances overall cybersecurity awareness.

V. PROPOSED SYSTEM WORK FLOW

The proposed system, Kavach, follows a structured workflow to detect and analyze cyber threats from emails, URLs, and QR codes in real time. The process begins when the user logs into the system through a secure web-based interface. After authentication, the user selects the desired module—Email IDS, URL IDS, or QR Code IDS—and provides the required input, such as email credentials, a web link, or a QR code image.

For the Email IDS module, the system connects to the user's mailbox using the IMAP protocol and retrieves recent emails.

It then extracts relevant information such as subject, sender, content, and attachments, which are analyzed using keyword-based and attachment-based detection techniques. In the URL IDS module, the entered link is sent to the VirusTotal API, where it is scanned by multiple security vendors to determine its safety. Similarly, in the QR Code IDS module, the uploaded or scanned QR code is decoded using OpenCV to extract the embedded URL, which is then analyzed using the same URL detection mechanism.

After processing the input, the system classifies the result as Safe, Suspicious, or Malicious and displays it on the dashboard along with detailed insights. The results are also summarized using graphical representations such as pie charts, and users are provided with options to export reports in CSV and PDF formats. This workflow ensures efficient, real-time, and multi-layer detection of cyber threats, enhancing user awareness and security.

VI. SYSTEM ARCHITECTURE

The proposed system, Kavach, follows a multi-layered architecture designed to detect cyber threats from emails, URLs, and QR codes through a centralized web-based platform. The architecture consists of four main components: the User Interface Layer, Processing Layer, Detection Engine, and External Threat Intelligence Integration.

The User Interface Layer provides a web-based dashboard developed using HTML, CSS, and JavaScript, where users can securely log in and interact with different modules such as Email IDS, URL IDS, and QR Code IDS. This layer ensures user authentication and smooth interaction with the system.

The Processing Layer, implemented using the Flask framework in Python, handles user requests and routes them to the appropriate modules. It processes inputs such as email

to fetch emails. For the QR IDS module, OpenCV is used to decode QR code images and extract embedded URLs.

The Detection Engine is responsible for analyzing the collected data and identifying potential threats. It uses keyword-based and attachment-based analysis for emails, while URLs extracted from both direct input and QR codes are analyzed using the VirusTotal API. This ensures accurate classification of threats as Safe, Suspicious, or Malicious.

Finally, the External Threat Intelligence Layer integrates third-party services such as VirusTotal, which aggregates security analysis from multiple antivirus engines to enhance detection accuracy. The results are then sent back to the dashboard, where they are displayed along with visual summaries and options to export reports in CSV and PDF formats.

This layered architecture ensures modularity, scalability, and efficient real-time detection of cyber threats across multiple vectors.

VII. METHODOLOGY

- 1) **User Authentication:** The user securely logs into the system using registered credentials.
- 2) **Module Selection:** The user selects the desired module such as Email IDS, URL IDS, or QR Code IDS from the dashboard.
- 3) **Input Submission:** The system accepts input in the form of email credentials, a URL, or a QR code image.
- 4) **Data Processing:** The backend processes the input by fetching emails, validating URLs, or decoding QR codes using appropriate techniques.
- 5) **Threat Analysis:** The detection engine analyzes the data using keyword-based rules and external threat intelligence APIs.
- 6) **Classification:** The system classifies the input as Safe, Suspicious, or Malicious based on analysis results.
- 7) **Result Display:** The analyzed results are displayed on the dashboard along with detailed information and visual summaries.
- 8) **Report Generation:** The system allows users to export the results in CSV and PDF formats for further use.

VIII. IMPLEMENTATION

- **Python Flask:** Used for backend development and handling application logic.
- **SQLite:** Used as a database for storing user authentication data.
- **OpenCV:** Used for decoding QR codes and extracting embedded URLs.
- **VirusTotal API:** Used for analyzing URLs and detecting malicious threats.
- **HTML, CSS, JavaScript:** Used to design the frontend interface and improve user interaction.

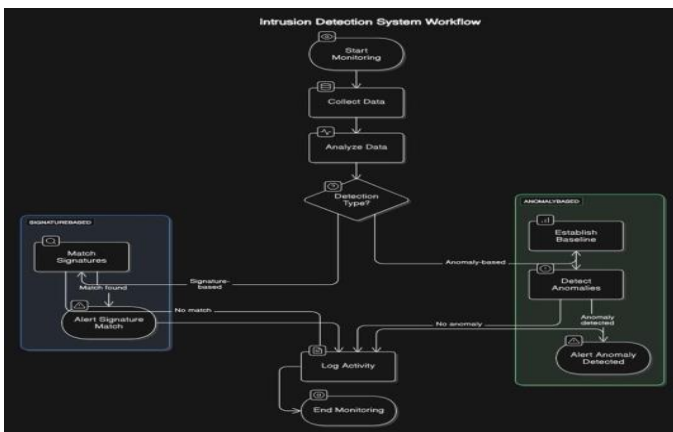


Fig. 4. System Architecture of the Proposed IDS

credentials, URLs, or QR code images. For the Email IDS module, the system connects to the Gmail server using IMAP

IX. RESULTS AND ANALYSIS

The system was tested with multiple inputs across different modules, and the results are summarized in Table I.

TABLE I
RESULTS OF IDS MODULES

Module	Input Tested	Detected	Accuracy
Email IDS	20 emails	12 suspicious	60 %
URL IDS	10 URLs	7 malicious	70 %
QR IDS	5 QR codes	4 detected	80 %

Accuracy is calculated using:

$$\text{Accuracy} = (\text{Correct Detections} / \text{Total Inputs}) \times 100$$

The results indicate that the system performs effectively in detecting threats across different modules.

X. ADVANTAGES

The proposed system offers several benefits:

- **Multi-layer Detection:** Provides protection across emails, URLs, and QR codes.
- **Real-time Analysis:** Detects threats instantly, minimizing risk.
- **User-friendly Interface:** Web-based dashboard enables easy scanning and result viewing.
- **Report Generation:** Supports CSV and PDF exports for documentation and analysis.
- **Integration with Threat Intelligence:** Uses VirusTotal API to enhance detection accuracy.

XI. LIMITATIONS

The proposed system has certain limitations:

- **Dependence on External API:** Relies on VirusTotal API for URL and QR analysis, requiring internet and subject to rate limits.
- **Basic Detection Logic:** Email module uses keyword and attachment rules, which may miss sophisticated phishing attacks.
- **Limited Dataset Testing:** Tested on a small number of emails, URLs, and QR codes; performance may vary for larger datasets.
- **No Advanced Machine Learning:** Lacks AI/ML models, limiting adaptability against new and evolving threats.

XII. CONCLUSION AND FUTURE SCOPE

The proposed system, Kavach, provides a multi-layer intrusion detection solution capable of analyzing emails, URLs, and QR codes in real time. It effectively identifies suspicious and malicious content, enhancing user-level cybersecurity and awareness. The system's web-based interface and report generation features make it practical and easy to use for individuals and small organizations.

For future work, the system can be enhanced by

integrating machine learning and AI models to detect sophisticated and zero-day attacks.

Expanding the dataset and incorporating real-time enterprise-level monitoring will improve scalability and robustness. Additionally, integration with cloud platforms and Security Information and Event Management (SIEM) can make Kavach suitable for large-scale deployments. The proposed system demonstrates the importance of user-level intrusion detection in addressing modern cyber threats that bypass traditional network-based security mechanisms.

Integrating multiple detection layers into a single platform enhances user awareness and proactive defense capabilities. Furthermore, the system highlights the potential of combining lightweight security solutions with real-time threat intelligence to create scalable and efficient cybersecurity frameworks suitable for both individuals and small organizations.

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Constant Current Boost Converter for Auxiliary Battery Charging in Electric Vehicles

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Abstract— As the world is shifting to EV transportation, the requirement for charging methods that are fast, efficient, and won't wear out batteries too quickly is also rising. Different approaches exist, and each has its own set of trade-offs. Some prioritize speed others focus on battery health, and a few try to balance both. The proposed system dives into the design and simulation of a lithium-ion battery charging system for electric vehicles. This paper presents the design and simulation of a DC-DC boost converter stepping up voltage from 12V to 16.8V for a 4.5Ah battery pack. Boost converter parameters including inductor, capacitor, and switching device are designed for continuous conduction mode operation at a specified switching frequency. A proportional-integral (PI) controller employing negative feedback control regulates the constant current-constant voltage charging by sensing battery current and computing the duty cycle. Simulation is carried out using MATLAB Simulink to observe the ripple voltage spikes across the output voltage by changing the switching frequency. Results show us that at 35KHz we got the least ripple voltage compared to other frequencies on which the system was tested.

Keywords— DC-DC Boost Converter, Lithium-ion Battery Charging, Constant Current-Constant Voltage Control, PI Controller, Electric Vehicle, Continuous Conduction Mode, 4S1P

I. INTRODUCTION

Today, the demand for Energy in this changing world has increased so much and most of it still comes from the traditional fossil fuel and produce harmful gases like CO₂, SO₂, NO₂, and other components, the best example of this is a coal power plant. Transportation is also an important factor which is responsible for increasing pollution that creates 24% of the world's Carbon Dioxide. So, promoting electric vehicles in more use is the best way for this situation to reduce the pollution.[1] Electrifying vehicles can be one of the most smartest way to cut the emissions.

Electric vehicles (EVs) are now the king of the sustainable transport over the traditional ones. They not only reduce the emissions, they also make it easier to run on renewable energy.[2] Also most of the people think that everything is just Battery and Motor, but it's more beyond that. EVs do generally rely on a interconnected system of smaller, auxiliary electrical systems—lighting, climate control, infotainment, control units, power steering, braking, and advanced driver assistance(ADAS). Each of these needs its own power, separate from the main high-voltage battery. That's where the auxiliary battery comes in, usually running

at 12V or 48V. Dedicated DC-DC converters step down power from the main battery (which can range from 200V to 800V) to these lower voltages.[3]

Lithium-ion batteries have taken over as the go-to choice for these auxiliary systems in the recent years. They win on energy density, cycle life, and low self-discharge.[4] A typical 4-series battery pack gives a nominal 14.8V and charges upto 16.8V. But lithium-ion batteries are a bit tricky to charge, we need to have to follow the Constant Current-Constant Voltage (CC-CV) protocol to keep them safe and working well.[5]

At the core of battery charging, DC-DC boost converters make everything run smoothly. They change power between multiple voltages using an inductor, a controlled switch which is usually a MOSFET, a diode, and an output capacitor.[6] The switch's duty cycle, managed through pulse-width modulation, sets the output voltage.[7] For control, Proportional-Integral-Derivative is the most favoured option. It's popular because it's straightforward to tune and works easily across many devices of power electronics system.[9]

Even with all the research on DC-DC converters and battery charging, some important issues are still pending. Most studies don't give much importance on voltage regulation, instead they focus on constant current control, which is critical for the CC phase of lithium-ion charging.[13] On top of that, traditional designs tend to produce a lot of output ripple voltage. That ripple can heat things inside the circuit, making the system less efficient, and trigger battery management protections. Few have focused on converters specifically optimized for charging auxiliary batteries in EVs.[14]

This paper aims on solving those problems. It presents a new constant current boost converter designed just for EV auxiliary battery charging. The main breakthrough is a PID-based constant current control strategy that slashes output ripple voltage compared to standard approaches. That means better charging quality and longer battery life. The research uses MATLAB/Simulink modeling and simulation to design, analyze, and test the system for charging a 4S lithium-ion auxiliary battery. Key contributions include mathematical modeling, a step-by-step design process for the constant current boost converter, a PID controller aimed at minimizing ripple, a detailed comparison showing how much ripple gets reduced, and practical design guidelines for EV auxiliary batteries.

II. RELATED WORK

Researchers had worked and practiced to how DC-DC boost converters work in electric vehicle (EV) auxiliary battery charging systems. There are many studies on this, they include everything from the nuts and bolts of design to advanced control strategies and even custom strategies meant just for battery charging.

We can refer an example, Dadhaniya [1]. They showed us bridgeless upgraded boost converter for EV battery charging. By cutting out the diode bridge rectifier at the front end, they cut conduction losses and managed to increase overall efficiency. Not only they met the IEC 61000-3-2 power quality standards, they nearly hit unity power factor, and THD was under 5%. On the other side, Khalil and Batarseh [2] got into bidirectional power flow. Their work, built on MATLAB/Simulink simulations, showed why bidirectional converters matter so much for regenerative braking and vehicle-to-grid (V2G) systems. They didn't just design a converter—they drilled down into how to choose a topology and what kind of control you need for smooth bidirectional power transfer. Core design methods for boost converters are well documented these days. Mahmor et al. [3] laid out a comprehensive approach using MATLAB Simulink, focusing on continuous conduction mode. They gave clear steps for picking out components—things like inductor and capacitor sizing, all based on ripple specs. To make sure their approach held water, they compared theory with simulation, and the numbers lined up closely. Nasrullah et al. [4] built on these simulation-driven designs by comparing mathematical modeling with circuit-based approaches in Simulink MATLAB. Their takeaway? Mathematical models nail the steady-state output, but if you want a better handle on real-world switching losses and transients, circuit-based models with MOSFET characteristics are the way to go. This kind of detail matters when you actually build hardware.

When it comes to control, researchers have pushed past basic linear techniques. Nik Ismail [5] tried out fuzzy logic control for DC/DC boost converters and found it handled dynamic changes better—faster settling, less overshoot, and more stability, especially in nonlinear settings where parameters can shift around. Then there's the work by Rao [6], who zeroed in on constant current charging. They used a PI controller with negative feedback, constantly comparing actual and reference battery current to keep charging steady. Their approach kept the charging current on target, with only minor deviations, and they covered everything from component values to different battery chemistries. Depending on the battery type, charging a 50 Ah cell took anywhere from 3.46 to 5.33 hours.

The currently existing and the developing designs of boost converter converters for battery charging has also led to new bidirectional designs. Sreejyothi[7] created a bidirectional charger using a buck-boost converter and PI feedback loop for the control mechanism. Their simulations showed reliable current regulation for a 50 Ah, 12V battery, even when the input supply was not constant.

Pushing into renewable energy territory, Dhillon [8] designed a photovoltaic system with battery storage, all tied together with a bidirectional DC-DC converter in MATLAB Simulink. Their work tackled the ups and downs of

renewable sources and the challenges of managing distributed energy storage.

All in all, the field keeps moving forward, blending new topologies, smarter control, and simulation-driven design to make EV charging more efficient and reliable. Al-Nussairi and Bayindir [9] took a close look at system stability in boost converters that feed battery loads, especially when those loads need constant power. They pointed out how tightly regulated loads can throw off stability because of negative incremental resistance. To solve this problem, they switched to fuzzy logic control, which improved the system stability even as the load shifted.

For cases where the output voltage needs to stay steady, Masri and Chan [10] designed a DC-DC boost converter with voltage feedback control. Their setup held the output at 24V, no matter if the input dropped as low as 6V or climbed up to 23V. The result was a converter that stayed reliable across that wide input range. Researchers have kept pushing on controller design, aiming to squeeze better performance out of boost converters. Adnan[11] ran simulations comparing PID control to open-loop operation, and the difference was clear. With PID, overshoot dropped, settling time shortened, and steady-state accuracy improved—far better than what they saw with an uncontrolled converter.

Hasaneen and Mohammed [12] while proceeding further, they laid out a full design process for boost converters. They covered everything: mathematical modeling, picking the right components, analyzing how the converter operates, and running simulations. Their focus was on converters for photovoltaic applications, and they checked performance under different radiation and temperature conditions.

There's also been a lot of work on new converter topologies. Santos de Carvalho [13] introduced a symmetrical interleaved coupled-inductor boost converter with clamp circuits. By interleaving, they cut down current ripple and boosted power density.

García-Vite[14] took a different route and came up with a flying capacitor double dual boost converter, which uses multi-level switching to push voltage gain higher while reducing stress on components. Meanwhile, Hinov[15] tackled the math behind high step-up boost converters, developing models that helped design passive components for better transient response and dynamic performance. Altogether, this body of research gives a strong foundation for using boost converters in electric vehicle auxiliary battery charging. From basic design to advanced control and new topologies, these studies move the technology forward—making power conversion more efficient, more stable, and smarter for automotive applications

III. METHODOLOGY

A. Working Principle

A boost converter stores energy in its inductor when the switch is on, then transfers that energy out to the load when the switch is off. This is how it manages to increase the output voltage above the input voltage. For EVs, this circuit is too important for charging auxiliary batteries. It has to shift easily between two modes to be able to achi the strict standards set for lithium-ion charging.

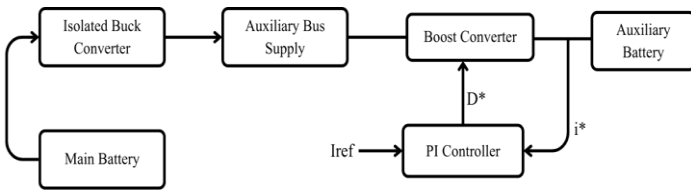


Figure 1. Block Diagram

In constant current mode, a PI controller checks the inductor current. It constantly changes the switching duty cycle, using the gap between the required and actual current, to make sure charging is on required target, even as battery voltage changes. This keeps the current steady during the main charging stage, keeping current ripple down, reducing voltage ripple at the battery.

Once the battery's almost full, things switch to constant voltage mode. Now, the PI controller keeps the output voltage right at the battery's safe upper limit. As the battery reaches full charge, current decreases gradually. In both charging modes, the PI controller reacts fast to any changes and removes steady-state issues, which is key for auxiliary battery systems. Power quality isn't just a technical detail here, it directly impacts everything from vehicle electronics to infotainment and safety gear, battery, motor and everything.

TABLE I. DESIGN PARAMETERS

Sr. No.	Parameters	Values
1	Power (P)	33.6 W
2	Output Voltage	16.8 V
3	Output Current	2 A
4	Input Voltage	12 V
5	Input Current	3.29 A
6	Switching frequency	25 KHz

B. Mathematical Equations

The voltage conversion equation can be rearranged to get the Duty cycle for boost converter. The output voltage is inversely proportional to (1 - D):

$$D = 1 - \frac{V_{in}}{V_{out}} \quad (1)$$

The inductor value is depended upon ripple current and ON period:

$$L = \frac{V_{in} * D}{\Delta I_L * f_s} \quad (2)$$

The output voltage ripple is limited to 1% of nominal output voltage. Exceeding this ripple level increases capacity fade and leads to potential safety risks.

$$C_{out} = \frac{I_{out} * D}{\Delta V_{out} * f_s} \quad (3)$$

Crossover frequency is important for adjusting loop responsiveness and stability. Greater bandwidth causes noise amplification and potential instability, while less bandwidth produces not good transient response. Standard practice selects the crossover frequency as 1/10 of the switching frequency to ensure adequate phase margin and avoid coupling with switching harmonics:

$$f_c = f_s / 10 \quad (4)$$

Converting the crossover frequency to angular frequency:

$$\omega_c = 2\pi \times f_c \quad (5)$$

The DC gain of the boost converter from the small-signal model is:

$$K_{dc} = V_{in} / (1 - D_{max}) \quad (6)$$

The proportional gain is calculated to get required crossover frequency through:

$$K_p = (\omega_c \times L) / K_{dc} \quad (7)$$

The integral gain is then calculated as:

$$K_i = K_p \times \omega_z \quad (8)$$

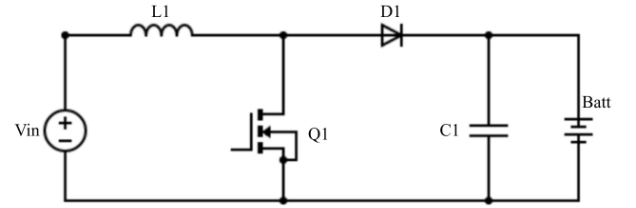


Figure 2. Circuit Diagram

TABLE II. CALCULATED PARAMETERS

Sr. No.	Parameters	Values
1	Inductor	150 μ H
2	Capacitor	68 μ F
3	Proportional(Kp)	0.14
4	Integral(Ki)	220

IV. SIMULATION

We designed and tested a constant current boost converter system in MATLAB Simulink, using the Simscape Specialized Power Systems library. We had to check how the converter handles ripple voltage when charging auxiliary batteries in electric vehicles. The simulation model included the inductor and capacitor for storing and smoothing energy, MOSFET switches, and a battery model. We set up 2 separate PI controller in a closed loop to handle both CC and CV charging. Discrete filter block for proper signal sampling and processing. For switching, We used a PWM generator, and constant blocks for providing the reference to PI controller. We also wrote a custom MATLAB which transitions from constant current to constant voltage mode, based on the battery's voltage.

To see how switching frequency affects ripple voltage, we ran simulations from 20 kHz to 50 kHz, frequencies normally found in power electronics. These choices help balance switching losses with the need for effective filtering. With this setup, we were able to go in to see how inductor current ripple, output voltage ripple, and the system's response change with different switching frequencies. The data gave a way for how tuning the switching frequency impacts charging performance in EV aux battery systems.

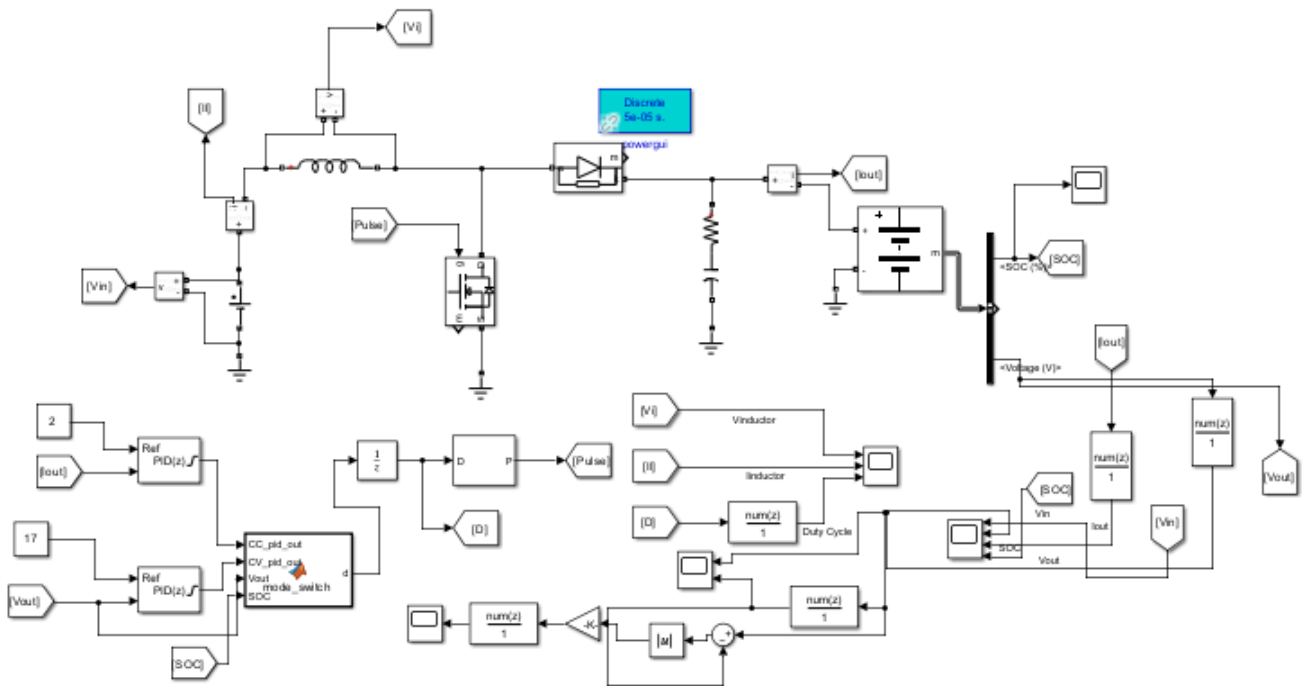


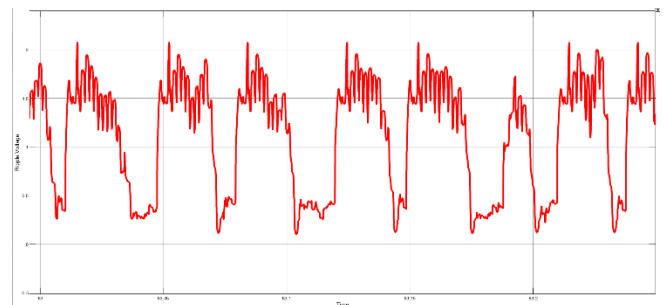
Figure 3. Simulation Diagram

V. SIMULATION RESULTS

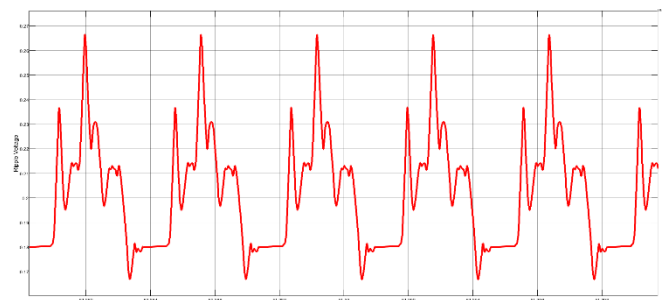
We simulated the constant current boost converter in MATLAB using the Simscape. The setup involved a 12V input and a 4S lithium-ion battery pack of 4.5Ah capacity, with motive of charging at 2A constant current. We ran multiple simulations, adjusting the switching frequency from 20 kHz up to 50 kHz, stepping up in 5 kHz increments. The baseline for comparison was 25 kHz. For control, we tuned the PI controller with K_p at 0.14 and K_i at 220, aiming for tight current regulation and minimal steady-state error during charging.

The ripple voltage data told an interesting story. Results depended heavily on switching frequency. At the lowest setting, 20 kHz (see Figure 4a), ripple voltage peaked at 1.0%. Bumping the frequency to 25 kHz (Figure 4b) dropped ripple to 0.22%. The sweet spot came at 30 kHz (Figure 4c), with ripple hitting a minimum of 0.19%—that's an 81% cut from the 20 kHz baseline. But after 30 kHz, things got less predictable. Ripple climbed to 0.29% at 35 kHz (Figure 4d), spiked at 0.47% for 40 kHz (Figure 4e), and settled at 0.38% by 50 kHz (Figure 4f). Pushing frequency higher didn't keep helping; instead, it brought diminishing returns for ripple reduction and increased the MOSFET switching losses.

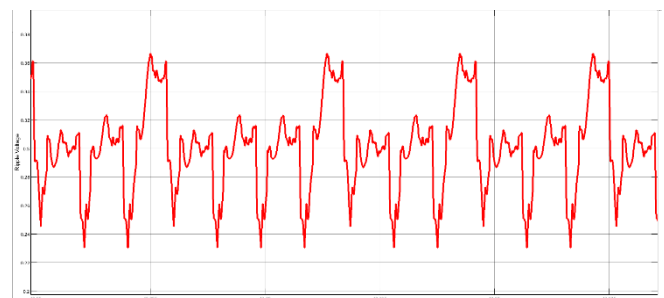
When we compared all the results (Figures 4a–4f, Figure 5), we came to an conclusion. For this auxiliary battery charging setup in electric vehicles, 35 kHz is the best option, low ripple without excessive switching losses.



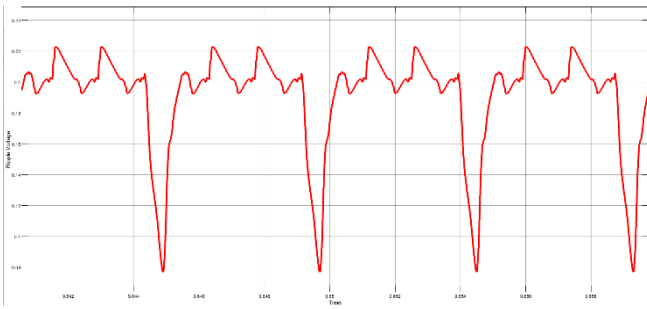
a. Switching frequency of 20KHz



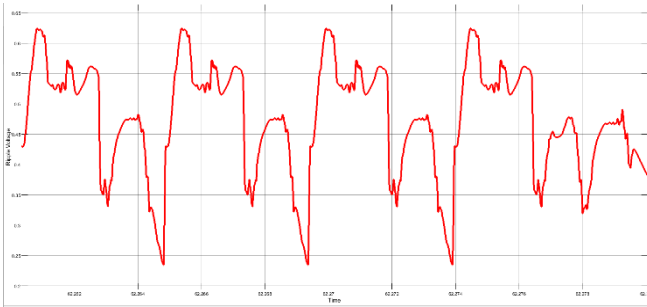
b. Switching frequency of 25KHz



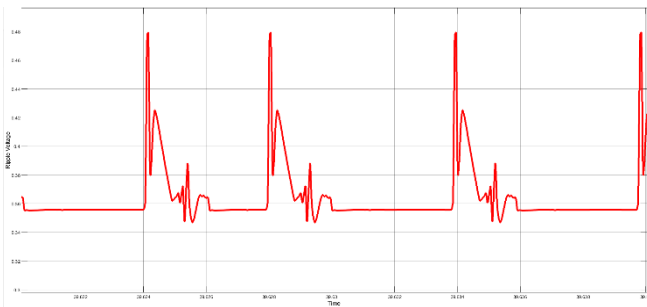
c. Switching frequency of 30KHz



d. Switching frequency of 40KHz



e. Switching frequency of 45KHz



f. Switching frequency of 50KHz

Figure 4. Simulation results of ripple voltage at various switching frequencies

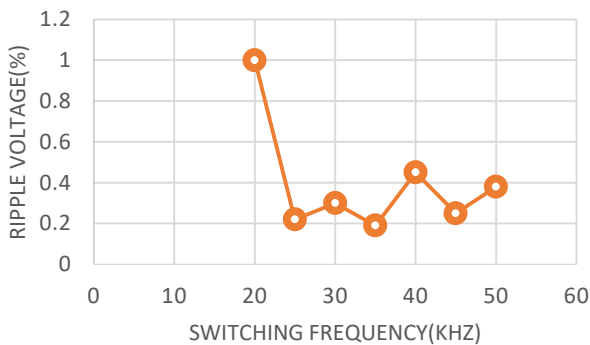


Figure 5. Switching frequency vs Ripple Voltage

VI. CONCLUSION

In this paper we have included the entire design and implementation of a constant current boost converter for aux battery charging in EVs, checked with help of MATLAB/Simulink simulation software with calculated values of passive components (150 μ H inductor, 220 μ F capacitors), MOSFET, and a PID controller. The designed converter was successfully implemented in

MATLAB/Simulink giving smooth battery voltage transition, CC-CV mode transition, and current regulation at the 2A setpoint. An important thing to note was found while checking the switching frequency impact on output voltage ripple: while the initial design used 25 kHz switching frequency as required, simulation across 20 kHz to 50 kHz gave optimal performance at 35 kHz with output voltage ripple minimized to 0.19%, pretty low than the 1% design specification, which shows can there can be simulation variations.

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DESIGN AND IMPLEMENTATION OF A HYBRID SOLAR–GRID WIRELESS ELECTRIC VEHICLE CHARGING STATION WITH IOT-BASED INTELLIGENT ENERGY MANAGEMENT

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Abstract- The rapid growth of electric vehicles has significantly increased the demand for safe, efficient, and sustainable charging infrastructure. Conventional plug-in charging systems suffer from mechanical wear, safety risks in outdoor environments, and heavy dependence on grid electricity. This paper presents the design and implementation of a Hybrid Solar–Grid Wireless Electric Vehicle Charging Station integrated with IoT-based intelligent power management. The proposed system utilizes magnetic resonant coupling for contactless power transfer, ensuring enhanced user safety and reduced maintenance. Solar energy is employed as the primary power source to promote sustainability, while grid supply serves as a backup to ensure uninterrupted charging during low solar conditions. An ESP32 microcontroller performs real-time monitoring of voltage and current parameters, executes automatic source selection through relay-based switching, and transmits operational data to a cloud platform via Wi-Fi for remote supervision. Experimental validation of the prototype demonstrates stable wireless power transfer, seamless solar–grid transition, and reliable real-time monitoring. The developed system offers a smart, scalable, and environmentally friendly solution for next-generation EV charging infrastructure.

I. INTRODUCTION

The global transition toward sustainable transportation has accelerated the adoption of electric vehicles (EVs) as an alternative to conventional internal combustion engine vehicles. Governments and industries worldwide are promoting EV deployment to reduce greenhouse gas emissions, decrease fossil fuel dependence, and improve urban air quality. However, the rapid growth of EVs has created a significant demand for efficient, reliable, and safe charging infrastructure.

Conventional EV charging systems primarily rely on wired plug-in connections. Although widely used, these systems present several limitations. Frequent plugging and unplugging causes mechanical wear of connectors, increasing maintenance requirements. Exposed cables may pose safety risks in outdoor environments, especially under wet conditions. In addition, most charging stations depend entirely on grid electricity, which often originates from non-renewable sources. This reduces the environmental benefits associated with electric mobility.

Wireless power transfer (WPT) technology offers a promising alternative to traditional wired charging. By using magnetic resonant coupling, electrical energy can be transferred between a transmitter and receiver coil without physical contact. This contactless approach improves user convenience, enhances safety, and reduces mechanical degradation. However, wireless charging systems require efficient power management and stable energy sources to ensure reliable operation.

Integrating renewable energy, particularly solar power, into EV charging infrastructure further enhances sustainability. Solar energy provides a clean and abundant power source during daytime operation. However, solar output is intermittent and depends on weather conditions and irradiation levels. A solar-only system may therefore fail to guarantee uninterrupted charging. To address this limitation, a hybrid solar–grid architecture can be implemented, where solar energy acts as the primary source and grid power serves as a backup during low solar availability.

In addition to renewable integration, intelligent monitoring and automation are essential for modern charging stations. The Internet of Things (IoT) enables real-time supervision of electrical parameters such as voltage, current, and power source status. Microcontrollers with integrated Wi-Fi capabilities, such as the ESP32, allow seamless communication with cloud platforms for remote monitoring, data logging, and performance analysis.

This paper presents the design and implementation of a Hybrid Solar–Grid Wireless Electric Vehicle Charging Station using magnetic resonant coupling and IoT-based intelligent power management. The proposed system prioritizes solar energy utilization, automatically switches to grid supply when required, and enables real-time monitoring through a cloudbased dashboard. The objective is to develop a smart, safe, and sustainable EV charging solution suitable for future smart city applications.

II. LITERATURE REVIEW

1. Dolf Gielen et al. This study discusses the global transition toward renewable energy systems and emphasizes the large-scale adoption of solar photovoltaic technology. It highlights the need to integrate renewable energy into transportation infrastructure to achieve long-term sustainability goals.
2. Wang et al. – Photovoltaic Energy Development The authors analyze advancements in photovoltaic technology and its growing economic feasibility. The study supports the

implementation of solar-based distributed generation systems for applications such as EV charging.

3. Liu and Wu :This research reviews advanced architectural glazing technologies aimed at improving energy efficiency in buildings. It supports the concept of energy-optimized infrastructure where renewable-powered EV charging systems can operate efficiently.
4. Ghosh and Norton: The study explores switchable glazing systems that reduce energy consumption in smart buildings. It demonstrates how adaptive energy control strategies can complement renewable-powered charging systems.
5. Kumar et al. – IoT Adoption Review :This paper provides a comprehensive review of IoT applications across industries. It highlights the importance of real-time monitoring, remote control, and cloud integration in smart energy systems.
6. Huang et al.:The authors propose IoT-based smart energy management frameworks for real-time data acquisition and system optimization. The research supports integrating IoT platforms into EV charging stations for performance monitoring.
7. Wang et al. – Vanadium Redox Flow Battery Study :This work focuses on battery management strategies for renewable-integrated systems. It emphasizes the importance of energy storage solutions in maintaining system stability when renewable sources fluctuate.
8. Saleem et al.:The study reviews IoT architecture and identifies communication and cybersecurity challenges. It stresses secure data transmission in cloud-connected smart energy systems.
9. Wang et al. – Hybrid Renewable Energy Systems :This reference discusses hybrid solar–grid configurations for reliable energy supply. It explains automatic source switching mechanisms to ensure uninterrupted power availability.
10. Kumar et al. – Smart Grid and IoT Integration :The authors analyze the integration of IoT with smart grid technologies. The study highlights intelligent monitoring, load management, and remote supervision as key features for next-generation charging infrastructure.

Novelty of work: The proposed work presents a novel integration of magnetic resonant wireless EV charging with a hybrid solar–grid energy architecture supported by IoT-based intelligent monitoring and control. Unlike conventional grid-dependent or standalone renewable charging systems, the developed system prioritizes solar energy utilization and automatically switches to grid supply when solar power is insufficient, ensuring uninterrupted operation. The use of an ESP32-based embedded controller enables real-time monitoring of voltage, current, power source status, and system performance through a cloud-connected platform. The design emphasizes low cost, modular implementation, improved safety through contactless charging, and enhanced energy optimization. By combining wireless power transfer, hybrid renewable integration, automatic source switching, and IoT-based remote supervision into a single coordinated prototype, the proposed system addresses existing gaps and offers a practical, scalable solution for sustainable EV charging infrastructure.

III. PROBLEM STATEMENT

- Existing EV charging stations primarily depend on grid electricity, increasing carbon emissions and operational costs.
- Conventional wired charging systems involve physical contact, leading to safety concerns, connector wear, and reduced user convenience.
- Standalone solar-based charging systems cannot ensure continuous operation due to the intermittent nature of solar energy.
- Lack of intelligent automatic switching between solar and grid supply affects system reliability and energy optimization.
- Limited integration of wireless charging, hybrid renewable energy management, and IoT-based real-time monitoring in a single system creates a gap in sustainable and smart EV charging solutions.

OBJECTIVES

- To design and develop a wireless EV charging system based on magnetic resonant power transfer.
- To integrate a hybrid solar–grid energy architecture that prioritizes renewable energy utilization.
- To implement an automatic source switching mechanism for uninterrupted charging operation.
- To develop an IoT-based real-time monitoring system using ESP32 for voltage, current, and power status tracking.
- To create a cost-effective, safe, and scalable prototype suitable for sustainable EV charging infrastructure.

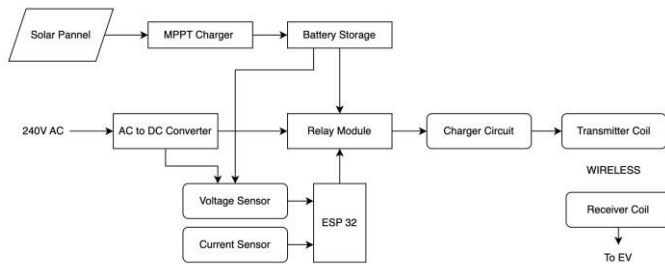
IV. RESEARCH METHODOLOGY

- **Literature Analysis:** Conduct a detailed review of existing research on wireless power transfer, hybrid renewable energy systems, and IoT-based smart energy management to identify technical gaps and system requirements.
- **System Design:** Develop the overall architecture of the hybrid solar–grid wireless EV charging system, including transmitter and receiver coils, power electronics, control unit, and IoT communication framework.
- **Hardware Implementation:** Design and assemble the prototype using solar panels, grid interface circuitry, magnetic resonant coils, rectification circuits, sensors, relays, and an ESP32 microcontroller for control and monitoring.
- **Software Development:** Program the ESP32 for automatic source switching, data acquisition, and cloud communication. Configure the IoT dashboard for real-time visualization of electrical parameters.
- **Testing and Performance Evaluation:** Conduct experimental testing under different operating conditions to evaluate charging efficiency, source switching performance, renewable energy utilization, and system reliability.

- **Data Analysis and Validation:** Analyze recorded data to assess system performance, compare with conventional approaches, and validate the effectiveness of the proposed hybrid wireless charging solution.

V. SYSTEM ARCHITECTURE

The proposed hybrid solar-grid wireless EV charging system is designed using a modular and integrated architecture to ensure reliability, safety, and intelligent energy management. The overall system is divided into five major subsystems: the Energy Generation Unit, Power Conditioning and Management Unit, Wireless Power Transfer Unit, Sensing and Control Unit, and IoT Communication Unit. Each subsystem performs a specific function while operating in coordination with the others.



1. Energy Generation Unit

This unit consists of two power sources: a solar photovoltaic (PV) panel as the primary renewable source and the utility grid as the secondary backup source. The solar panel converts sunlight into DC electrical energy. Since solar output varies with irradiance and weather conditions, the generated voltage is not constant. Therefore, the output from the PV panel is passed through a voltage regulation and filtering stage to stabilize the supply before feeding it into the main system. The grid supply acts as a backup source when solar energy is insufficient, such as during nighttime or low sunlight conditions. This dual-source configuration ensures continuous availability of power for EV charging.

2. Power Conditioning and Hybrid Energy Management Unit

This section is responsible for managing and regulating power from both sources. It includes:

- Voltage regulators
- Protection circuits
- Relays or switching devices
- Filtering components

The ESP32 microcontroller continuously monitors the solar voltage level. When sufficient solar power is available, the system prioritizes solar energy for charging. If the solar voltage drops below a predefined threshold, the controller automatically switches to grid supply using relays. This automatic hybrid switching mechanism eliminates manual intervention and ensures uninterrupted charging. It also optimizes renewable energy utilization by maximizing solar consumption before drawing power from the grid.

3. Wireless Power Transfer Unit

The regulated power is supplied to the transmitter section, which generates high-frequency alternating current. This AC signal energizes the transmitter coil to create a time-varying magnetic field. Using magnetic resonant coupling, energy is transferred wirelessly across an air gap to the receiver coil placed on the EV side. Because both coils are tuned to the same resonant frequency, efficient power transfer is achieved even with moderate alignment variation. The receiver coil captures the magnetic flux and converts it back into electrical energy. The received AC signal is then passed through a rectifier and filtering circuit to produce stable DC output suitable for charging the EV battery or load.

4. Sensing and Control Unit

To ensure safe and efficient operation, voltage and current sensors are installed at key points in the system, including:

- Solar panel output
- Grid input
- Transmitter side
- Receiver side

These sensors provide real-time electrical parameter measurements to the ESP32 microcontroller. The controller processes this data to manage source switching, monitor charging status, and detect abnormal conditions such as overvoltage or overcurrent.

5. IoT Communication and Monitoring Unit

The ESP32 microcontroller includes built-in Wi-Fi capability, enabling direct connection to a cloud-based IoT platform. Electrical parameters such as voltage, current, power source status, and charging condition are transmitted in real time to an online dashboard.

This allows:

- Remote monitoring of system performance
- Tracking renewable energy utilization
- Observing source switching status
- Data logging for analysis and validation

The IoT layer enhances transparency, enables smart supervision, and supports future scalability into smart grid or smart city applications.

Overall Working Integration

The system operates in a coordinated manner where solar energy is utilized as the primary source, grid power ensures backup reliability, wireless transfer enables safe contactless charging, and IoT monitoring provides intelligent supervision. The modular architecture ensures flexibility, cost effectiveness, and scalability, making the proposed system suitable for sustainable and next-generation EV charging infrastructure.

Overall System Overview

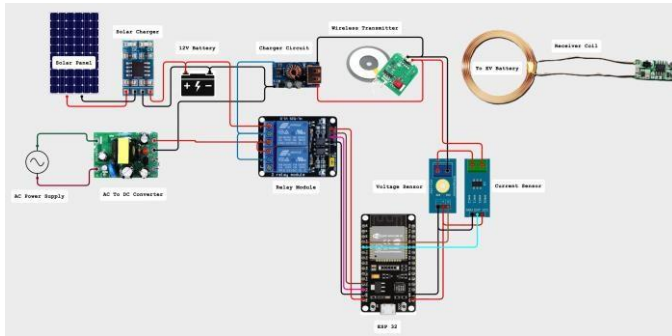
The system consists of four major functional blocks:

1. Hybrid Energy Source Unit (Solar + Grid)
2. Power Conditioning and Control Unit
3. Wireless Power Transfer Unit
4. IoT-Based Monitoring and Communication Unit

These subsystems operate in coordination to deliver regulated wireless power to the EV load while continuously monitoring system performance.

VI. Proposed System / System Design

The proposed system is a hybrid solar-grid based wireless electric vehicle charging station integrated with IoT-enabled intelligent monitoring. The system is designed to ensure sustainable energy utilization, uninterrupted operation, and safe contactless charging through magnetic resonant power transfer.



Hybrid Energy Source Unit

The primary energy source is a solar photovoltaic panel that converts solar energy into DC electrical power. Since solar output fluctuates with environmental conditions, the generated voltage is passed through a voltage regulation stage to stabilize the supply. A grid power connection is incorporated as a secondary backup source. When solar power is insufficient due to low irradiance or nighttime conditions, the system automatically switches to grid supply to maintain continuous charging.

Power Conditioning and Intelligent Control Unit

The power conditioning section includes voltage regulators, filtering circuits, protective elements, and relay-based switching mechanisms. The ESP32 microcontroller acts as the central controller of the system. The controller continuously monitors solar voltage levels using sensors. If the solar voltage is above a predefined threshold, the system prioritizes solar energy. If it drops below the required level, the controller activates relays to switch to grid power.

This automatic hybrid switching logic ensures maximum renewable energy utilization while maintaining reliable system operation.

Wireless Power Transfer Unit

The regulated power is supplied to a high-frequency inverter circuit that energizes the transmitter coil. The transmitter coil generates an alternating magnetic field at a specific resonant frequency. The receiver coil, placed on the EV side, is tuned to the same resonant frequency. Through magnetic resonant coupling, energy is transferred wirelessly across an air gap.

The received alternating signal is rectified and filtered to provide stable DC output suitable for charging the EV battery or connected load. This contactless charging mechanism eliminates physical connectors, reducing wear and improving safety.

Sensing and Protection Mechanism

Voltage and current sensors are installed at critical points in the system to measure:

- Solar panel output, Grid input, Transmitter side parameters and Receiver side charging output

The ESP32 processes this data to ensure safe operation and detect abnormal conditions such as overcurrent or voltage fluctuation.

IoT Monitoring and Communication Unit

The ESP32 microcontroller, equipped with built-in Wi-Fi capability, transmits real-time electrical parameters to a cloud-based dashboard. Users can remotely monitor voltage levels, current flow, power source status, and charging performance.

This IoT integration enhances system transparency, enables remote supervision, and supports data logging for further analysis and performance evaluation.

System Integration

The proposed system combines renewable energy prioritization, intelligent hybrid switching, efficient wireless power transfer, and IoT-based remote monitoring into a single integrated framework. The modular and scalable design makes it suitable for smart city applications and sustainable EV charging infrastructure.

VII. Experimental Setup and Implementation

The experimental setup was developed to validate the performance of the proposed hybrid solar-grid wireless EV charging system. A laboratory-scale prototype was constructed to demonstrate hybrid energy management, wireless power transfer, and IoT-based monitoring under controlled conditions.

6.1 Hardware Components

The prototype consists of the following major hardware components:

- Solar photovoltaic panel (primary renewable source)
- AC grid input with regulated power supply
- ESP32 microcontroller for control and communication
- Relay module for automatic source switching
- Transmitter and receiver coils for wireless power transfer
- High-frequency driver/inverter circuit
- Rectifier and filtering circuit on receiver side
- Voltage and current sensors
- Protection components such as fuses and regulators

All components were selected to ensure safe low-voltage operation suitable for experimental validation.

6.2 Hybrid Energy Integration

The solar panel output was connected to a voltage regulation circuit to stabilize fluctuations due to varying irradiance. The grid supply was stepped down and rectified to obtain regulated DC power compatible with the system.

Both sources were connected to a relay-based switching circuit controlled by the ESP32. A voltage sensor continuously

measured the solar output. When the solar voltage exceeded the predefined threshold, the controller selected solar as the active source. When the voltage dropped below the set level, the system automatically switched to grid power. This ensured uninterrupted charging during low sunlight conditions. **6.3**

Wireless Power Transfer Implementation

The wireless charging module was implemented using a pair of air-core copper coils designed for magnetic resonant coupling. The transmitter coil was driven by a high-frequency AC signal generated through an inverter circuit. Both transmitter and receiver coils were tuned to operate at the same resonant frequency to maximize power transfer efficiency. The receiver coil output was connected to a rectifier and capacitor filter circuit to convert the induced AC signal into stable DC output for the load. Performance testing was carried out by varying the air gap between the coils and observing output voltage and current levels.

6.4 Control and IoT Monitoring

The ESP32 microcontroller served as the central control unit. It performed the following tasks:

- Monitoring solar and grid voltage levels
- Controlling relay-based source switching
- Acquiring voltage and current data from sensors
- Transmitting real-time data to the IoT dashboard

The ESP32 was programmed using the Arduino IDE. Wi-Fi connectivity was configured to send system parameters to a cloud-based IoT platform for real-time visualization. The dashboard displayed voltage levels, current values, power source status, and overall charging condition.

6.5 Testing Procedure

The system was tested under different operating conditions:

- Solar-only operation
- Grid-only operation
- Automatic switching during solar voltage drop
- Different coil alignment and air gap variations

Electrical parameters were recorded and analyzed to evaluate system performance, efficiency, and reliability.

6.6 Prototype Validation

The experimental results confirmed that the system successfully prioritized solar energy, automatically switched to grid supply when required, and maintained stable wireless power transfer. Real-time IoT monitoring enabled continuous supervision and data logging, validating the feasibility of the proposed hybrid wireless EV charging architecture.

VIII. Conclusion

This research presents the design and implementation of a hybrid solar-grid based wireless electric vehicle charging system integrated with IoT-enabled intelligent monitoring. The proposed system successfully combines renewable energy utilization, automatic source switching, magnetic resonant wireless power transfer, and real-time remote supervision into a single coordinated platform.

The hybrid energy architecture ensures maximum utilization of solar power while maintaining uninterrupted charging through grid backup. The wireless charging mechanism improves safety and user convenience by eliminating physical

connectors and reducing mechanical wear. Additionally, the integration of an ESP32-based IoT framework enables real-time monitoring of electrical parameters, enhancing system transparency and operational control.

Experimental evaluation demonstrates the feasibility, reliability, and cost-effectiveness of the proposed prototype. The system offers a practical and scalable solution for sustainable EV charging infrastructure and supports the broader goal of reducing carbon emissions in transportation.

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Design and Implementation of a Raspberry Pi-4 GUI System for Steering Column Strength Test Rig as per AIS-075 and ECE R116

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Abstract— The steering column is a critical automotive safety component. It must ensure both driver protection and anti-theft security via a controlled yield and slip mechanism. Manual testing of the steering column often lacks the precision and repeatability required by the modern regulatory standards. This paper presents the design and development of a Raspberry Pi-4 based automated steering column strength test rig with a Graphical User Interface (GUI). The proposed solution utilizes an AC Servo motor with an integrated encoder, Torque Sensor and Raspberry Pi-4 controller with a custom PyQt5 Graphical User Interface for real-time data acquisition. Using a modular software architecture, the system enables precise measurement of slipping torque across an angular range of $+90^\circ$, -180° and $+90^\circ$. Experiments confirm a measurement accuracy of within $\pm 2\%$ and validate a minimum slipping torque of 100Nm. The developed system delivers an efficient, digitalized approach to automotive safety testing. It reduces human errors and boosts reliability in industrial quality assurance.

Keywords—Steering Strength Test Rig, Slipping Torque Measurement, Raspberry Pi-4, AIS-075 and ECE R116 Compliance, PyQt5 GUI, Anti-Theft Mechanism Validation, Automotive Safety Testing

I. INTRODUCTION

Steering columns play crucial role not only in vehicle control but also in ensuring driver safety and vehicle security. Modern steering columns are designed with integrated anti-theft locking mechanisms and energy-absorbing structures, which ensure protection against unauthorized use while minimizing driver injury during collision events. Regulatory standards such as AIS-075 and ECE R116 specify stringent requirements for steering locking systems, including their ability to resist external torque and prevent unintended rotation of steering wheel. [1], [2]

A key feature of steering column locking system is the slip and yield mechanism, which enables controlled under predefined torque conditions. Accurate measurement of this slipping torque is important to ensure compliance with AIS-075 and ECE R116. Early developments in this domain focused on anti-rotation locking devices with integrated torque-limiting features, designed to restrict excessive force transmission while maintain structural integrity and preventing component damage. [3]

Further advancements introduced dedicated test apparatus for evaluating steering column behavior under impact and load conditions, enabling assessment of energy absorption and deformation characteristics. [4] Additionally, studies on stick-slip behavior in steering systems have highlighted the influence of friction and contact dynamics on torque characteristics and system stability. [5]

Despite these developments, many industries still rely on manual or semi-automated testing methods, which are time consuming, prone to human error and lack of precision. Recent research has addressed these limitations through the use of embedded data acquisition systems and digital sensors. Low-cost platforms based on Raspberry Pi and Python enable real-time monitoring and control of test parameters [6]. Similarly, modern torque measurement systems employ high-precision sensors and signal processing techniques to accurately capture torque and rotational characteristics. [7]

In parallel, several industrial solutions and patented technologies have proposed automated test rigs and test benches for steering systems. The steering column slip endurance test rig presented in SAE research demonstrates the use of motor-driven actuation systems for evaluating slip behavior and durability under controlled conditions. [8] Furthermore, patent designs describe electric steering system test benches and comprehensive performance testing platforms, integrating motor drivers, loading systems and computer-based control for accurate and repeatable testing. [9], [10] Other studies have focused on component-level testing methods for steering column systems, particularly the evaluation of yoke clapping force, which is essential for ensuring structural integrity, mechanical reliability and proper assembly. [11]

However, most existing solutions are either expensive, or not easily accessible for small-scale or academic applications. This creates a need for a cost-effective, automated and accurate test system capable of meeting regulatory requirements while ensuring ease of operation.

To address this gap, this paper presents the design and development of a Raspberry Pi-4 based automated steering column strength test rig with a graphical user interface (GUI). The system utilizes an AC Servo motor with an integrated encoder and a torque sensor for real-time measurement. A custom-developed PyQt5-based GUI enables user interaction, real-time data visualization and automated report generation. The proposed system ensures high accuracy, repeatability and compliance with AIS-075 and ECE R116

standards, while significantly reducing dependency on manual testing methods.

The developed test rig provides a reliable and cost-effective solution for evaluating steering column performance, contributing to improved safety validation processes in the automotive industry.

II. METHODOLOGY

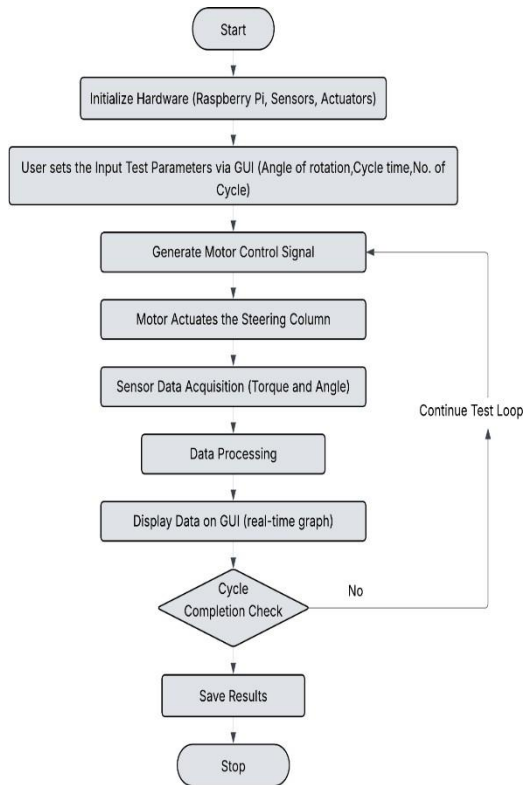


Figure-1 Workflow Diagram

The developed GUI control system automates the steering column strength testing process using a Raspberry Pi 4 platform. The workflow of the system is illustrated in Figure-1. Initially, the system performs hardware initialization where the Raspberry Pi establishes communication with peripheral devices such as sensors and the motor driver through configured GPIO interfaces and communication protocols. After successful initialization, the operator enters the required test parameters through the GUI, including steering angle limits (+90°, -180°, +90°), cycle time (20 ± 2 seconds), and the total number of test cycles (5). Based on these user-defined parameters, the control software generates appropriate motor control signals, which are transmitted to the motor driver to actuate the motor responsible for rotating the steering column within the specified angular limits. During the testing process, sensors continuously acquire real-time physical parameters such as slipping torque and angular displacement of the steering column. The acquired sensor signals are then processed by the Raspberry Pi 4 to convert raw electrical signals into meaningful engineering units and to eliminate noise or fluctuations through basic signal conditioning techniques. The processed data is displayed on the GUI in the form of real-time graphs and numerical indicators, enabling the operator to monitor the test progress

dynamically. The system also performs a total of 5-cycle completion check as per standard to determine whether the predefined number of testing cycles has been achieved. If the required cycle count has not been completed, the system continues the testing loop by generating subsequent motor control signals and repeating the measurement process. Once the specified number of cycles is completed, the system terminates the test sequence and stores the recorded data in a structured format for further analysis and documentation. This automated methodology improves testing efficiency, ensures accurate data acquisition, and enables reliable monitoring of steering column strength during the testing process.

A. GUI Design and Development

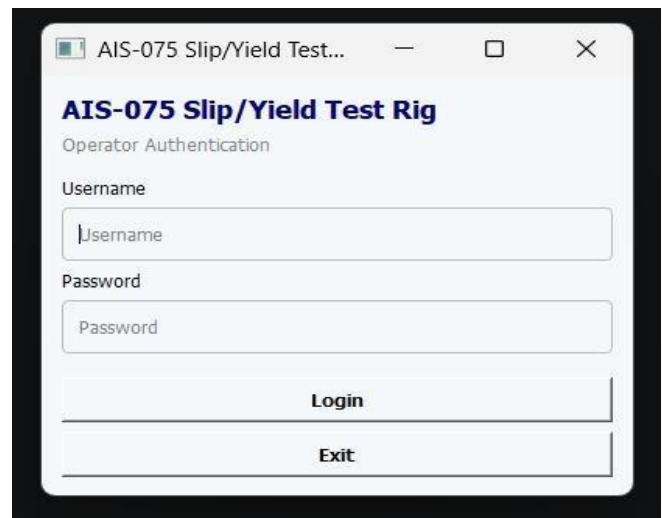


Figure-2.1 Operator Authentication login page

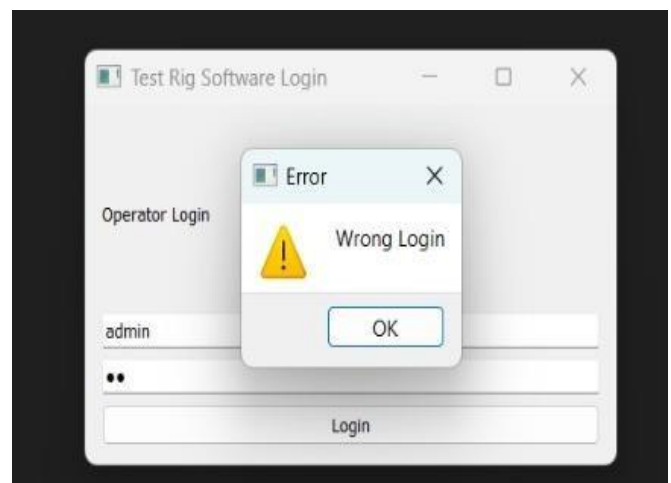


Figure-2.2 Unauthorized login page

The software was developed using the PyQt5 framework in Python, providing a robust environment for multi-threaded operations. The interface is divided into three functional modules:

- **Security and Setup:** A secure login window ensures that only authorized personnel can access the test rig. Refer to Figures 2.1, 2.2 and 2.3. The setup interface allows the operator to input critical data,

including operator name, client details, and the specific details required for the test. Refer Figure-3

cycle, ensuring immediate feedback on part performance. Refer Figure-4

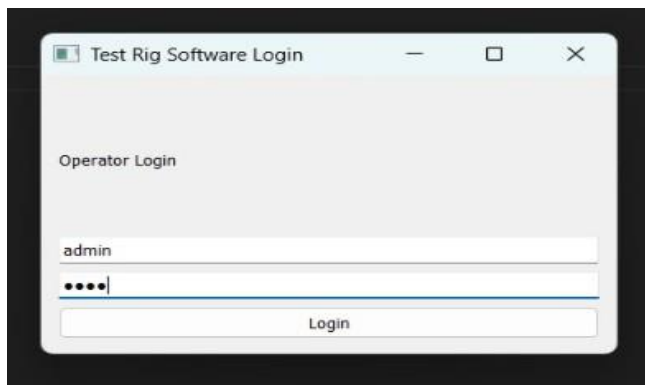


Figure-2.3 Authorized login page



Figure-4 Cycle Result Pop-Ups

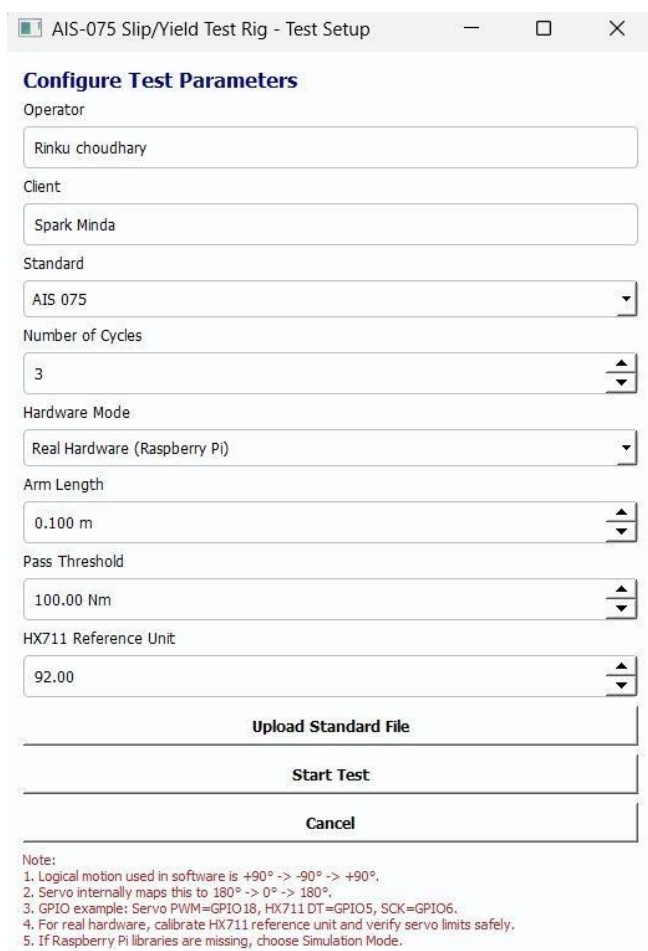


Figure-3 Test Setup Page

- **Real-time Visualization:** The main dashboard features an integrated Matplotlib canvas that plots Torque (Nm) and Angular Displacement (°) against Time (s). This enables the operator to visually monitor the "slip" behavior of the steering column during actuation. Refer Figure-5
- **Cycle Management:** A dedicated "Cycle Results" table logs peak torque values at specific angular positions (+90°, -180°, +90°) for every completed

B. Motor Control Algorithm

The motor control logic follows a deterministic sequence to ensure mechanical safety and precision. Upon initiating the "Start Cycle" command, the software executes the following algorithm:

Parameter Injection: The software reads the selected standard's limits and injects target angular positions into the AC Servo Motor's controller via serial communication.

Synchronized Actuation: The motor initiates a bi-directional sweep (typically from +90° to -180° and then to +90°). During this phase, the software continuously polls the torque sensor and encoder.

Safety Watchdog: The algorithm monitors the instantaneous torque; if values exceed the predefined structural safety limits of the steering column, the software triggers an emergency stop to prevent equipment damage.

Data Capture: At precisely defined angular intervals, the system captures torque snapshots to verify compliance with the minimum 100Nm slipping torque requirement.

III. RESULT AND DISCUSSION

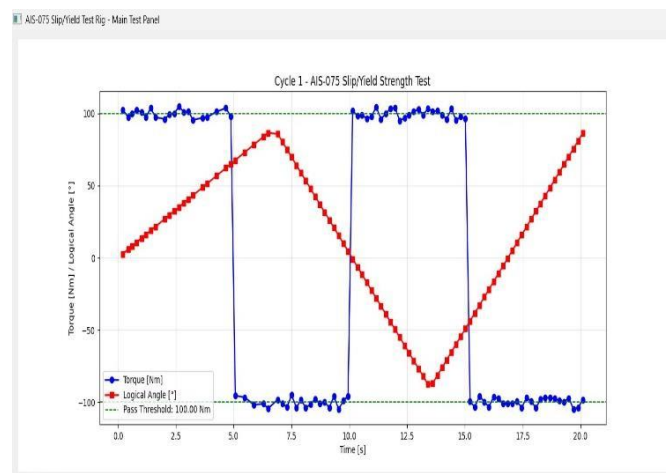


Figure-5 Torque and Angle Vs Time Graph

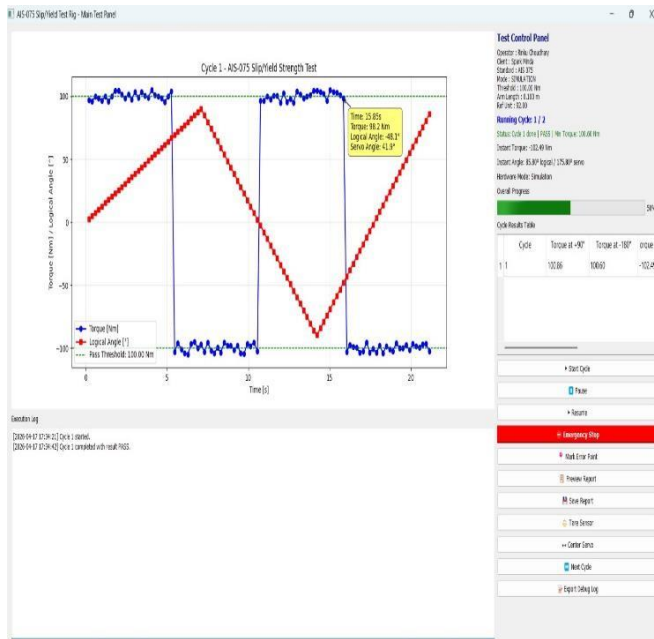


Figure-6 GUI Output Window

A. Real-Time Graphical Analysis of Torque and Angle

The operation of the developed system is primarily understood from the real-time graph displayed in the GUI. In the graph, torque is represented by the blue line and angular displacement by the red line, both plotted against time. Different colors are intentionally used so that both parameters can be easily distinguished during observation.

The red line follows a triangular pattern, which shows that the motor rotates the steering column in a controlled sequence: from 0° to +90°, then to -180°, and back to 0°. This ensures that the system is tested in both directions within a single cycle.

The blue line represents torque, and it rises quickly to around 104–105 Nm and then becomes almost constant. This flat region indicates the slip point, where the internal safety mechanism activates and prevents further increase in torque. Instead of increasing further, the torque stabilizes, which confirms safe operation. Also, the torque changes sign (positive to negative) when the direction of rotation changes, showing that the system responds properly in both directions. Refer Figure-6

B. Point-wise Observation using Tooltip Feature

To understand the system behavior more precisely, the GUI provides a tooltip (data marker) feature. By hovering over any point on the graph, exact values of time, torque, and angle can be observed. Refer Figure-6

For example, at one instant:

- Time ≈ 15.85 s
- Torque ≈ 98.2 Nm
- Angle ≈ 41.9°

This feature helps in analyzing the system at specific moments instead of only looking at overall trends. Such detailed observation is difficult to achieve in manual testing and improves the accuracy of analysis.

C. Other GUI Features

The system also includes several control and monitoring features such as Start, Pause, Resume, Emergency Stop, Mark Point, Preview Report, Save Report, etc. which are shown on the bottom-right of Figure-6. The Mark Point option allows the user to highlight important or abnormal points during testing. The GUI is designed to be user-friendly and suitable for real-time industrial use.

D. Cycle-wise Results and Automated Report Generation



Figure-7 Generated Report

The bottom part of the interface displays a Cycle Results table, where torque values at specific angles are recorded for each cycle. The table is structured to show values at +90° and -180° positions for multiple cycles.

From the observed data:

- Cycle 1: +90° → 100.86 Nm, -180° → 100.60 Nm, +90° → -102.49 Nm
- Cycle 2: +90° → 96.93 Nm, -180° → -101.74 Nm, +90° → -99.96 Nm

The values remain almost constant across all cycles, which indicates:

- Good repeatability
- Stable system performance
- Measurement accuracy within acceptable limits

If there were large variations, it would indicate instability or error, but here the consistency confirms reliable operation of the test rig. Refer figure-5

IV. CONCLUSION

This work presents the design and development of a Raspberry Pi-4 based GUI control system for a steering column strength test rig in accordance with AIS-075 and ECE R116. [1], [2] The proposed system utilizes a PyQt5-based GUI, an AC Servo motor with an integrated encoder and torque sensor to enable accurate and automated control of steering column testing.

Unlike traditional methods that depend heavily on manual operation, the proposed approach provides a more stable and reliable testing environment. Earlier works primarily focused on mechanical locking concepts and standalone testing setups. [3], [4], [5] Whereas the present system integrates control, measurement and data acquisition into a single platform. The use of embedded processing aligns modern trends in low-cost automation [6], while accurate torque sensing ensures dependable measurement outcomes. [7]

In comparison with the existing systems, which are often complex and expensive [8], [9], [10], the developed setup offers a simplified and economical alternative without compromising functionality. It also supports the need for precise component-level evaluation highlighted in recent studies. [11]

Overall, the system improves the consistency, usability and accessibility of steering column testing. It provides a practical solution for both academic and industrial applications, contributing to more efficient validation of automotive safety system.

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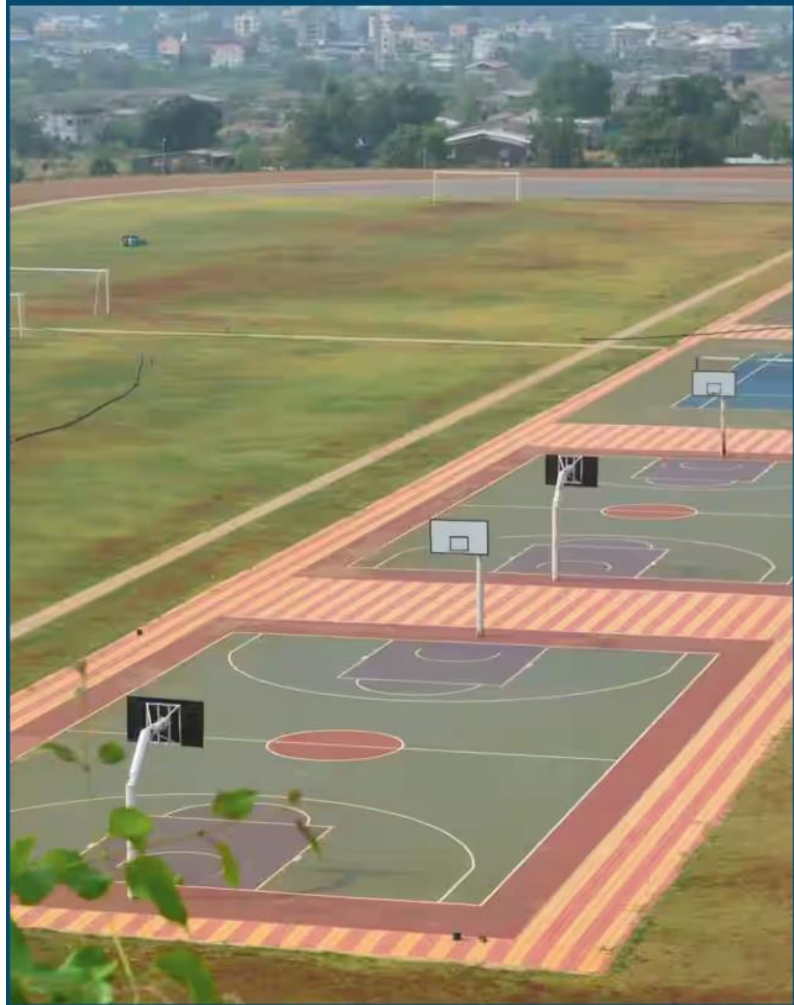


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