Visvesvaraya Technological University, Belagavi – 590018.

PROJECT REPORT
ON

AI-Powered EV Battery Fire Prevention System

Submitted in partial fulfillment for the award of degree of

BACHELOR OF ENGINEERING
in
ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted by

RASHMI RAO B	**4CB22EC035**
SAMARTHA R BHAT	**4CB22EC042**

Under the Guidance of

Mrs. Akshatha G Baliga
Assistant Professor, Department of Electronics & Communication Engineering

ELECTRONICS & COMMUNICATION ENGINEERING
CANARA ENGINEERING COLLEGE
(An Autonomous Institution, Under VTU, Belagavi and Recognized by AICTE, Accredited by NBA (CSE, ISE, ECE) and NAAC 'A' GRADE)
Sudhindra Nagar, Benjanapadavu, Mangaluru - 574219, Karnataka.

2025-26

CANARA ENGINEERING COLLEGE

(An Autonomous Institution, Under VTU, Belagavi and Recognized by AICTE, Accredited by NBA (CSE, ISE, ECE) and NAAC 'A' GRADE)

Sudhindra Nagar, Benjanapadavu, Mangaluru - 574219, Karnataka.

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

CERTIFICATE

Certified that the project work entitled **"AI-Powered EV Battery Fire Prevention System"** carried out by

RASHMI RAO B	**4CB22EC035**
SAMARTHA R BHAT	**4CB22EC042**

the bonafide students of VII semester ELECTRONICS AND COMMUNICATION ENGINEERING in partial fulfillment for the award of Bachelor of Engineering in ELECTRONICS AND COMMUNICATION ENGINEERING of the Visvesvaraya Technological University, Belagavi during the year 2025-2026. It is certified that all corrections/suggestions indicated for the internal assessment are as indicated during the internal assessment. The project report has been approved as it satisfies the academic requirements in respect of the project work prescribed for the said degree.

Mrs. Akshatha G Baliga
Project Guide

Dr. Raghavendra M Shetty K
HoD

Dr. Demian Antony D'Mello
Dean-Academics and Vice-Principal

Dr Nagesh H R
Principal

External Viva:

Examiner's Name	Signature with Date
1.	....
2.	....

CANARA ENGINEERING COLLEGE

(An Autonomous Institution, Under VTU, Belagavi and Recognized by AICTE, Accredited by NBA (CSE, ISE, ECE) and NAAC 'A' GRADE)

Sudhindra Nagar, Benjanapadavu, Mangaluru - 574219, Karnataka.

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

DECLARATION

We hereby declare that our entire work embodied in this Project Report titled **"AI-Powered EV Battery Fire Prevention System"** has been carried out at CANARA ENGINEERING COLLEGE, Mangaluru under the supervision of **Mrs. Akshatha G Baliga**, for the award of **Bachelor of Engineering** in **ELECTRONICS AND COMMUNICATION ENGINEERING**. This report has not been submitted to this or any other University for the award of any other degree.

RASHMI RAO B	**4CB22EC035**
SAMARTHA R BHAT	**4CB22EC042**

Acknowledgement

We dedicate this page to acknowledge and thank those responsible for the shaping of the project. Without their guidance and help, the experience while constructing the dissertation would not have been so smooth and efficient.

We sincerely thank our Project guide **Mrs. Akshatha G Baliga**, Assistant Professor, Electronics and Communication Engineering for his guidance and valuable suggestions which helped us to complete this project. We also thank our Project coordinators **Dr. Dayanand GK**, Dept of Electronics & Communication Engineering, for their consistant encouragement.

We owe a profound gratitude to **Dr. Raghavendra M Shetty K**, Head of the Department, Electronics and Communication Engineering, whose kind support and guidance helped us to complete this work successfully. We also take this opportunity to thank our Dean Academics and Vice-Principal **Dr. Demian Antony D'Mello** and we are extremely thankful to our Principal, **Dr Nagesh H R**, for their support and encouragement.

We would like to thank all faculty and staff of the Department of Electronics and Communication Engineering who have always been with us extending their support, precious suggestions, guidance, and encouragement through the project.We also express our gratitude to our beloved friends and parents for their constant encouragement and support.

RASHMI RAO B	**4CB22EC035**
SAMARTHA R BHAT	**4CB22EC042**

Abstract

Batteries for electric vehicles (EVs), including risks such as overheating, unstable voltage levels, and fires, are designed to address significant safety concerns. That firm introduces a software-based automated reasoning organization designed to improve EV battery safety by providing real-time fact monitoring, predictive information, and error detection. The solution has a synergistic splashboard evolved, the Stream-lit, showing indispensable parameters such as Charge, Wellness (SOH), Voltage, Current, and Temperature. It processes falsification detector data via Flask APIs and includes an essential safety feature, AES Encryption and Consumer Verification. The AI model, consolidated via APIs, identifies abnormal forms and anticipates potential explosion hazards. Although the prototype is online, it serves as a solid foundation for future safety structures in EV manufacturing, inquiry, and education.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Overview

A significant step forward for the planet's efforts to reduce carbon emissions and obtain renewable transport is the quick move to promote dynamic automobiles (EVs). The lithium ion battery, a crucial component of energy conservation and propulsion, is close to the EV enthusiasts. Still, progress on battery devices is one of the critical obstacles to battery safety, particularly with regard to thermal surges, voltage imbalances, and heat hazards. Battery management compositions (BMS) are traditionally used to monitor and control major battery parameters including voltage, temperature, charge state (SOC), and health (SOH). However, conventional BMS stages frequently do not have sophisticated features identical to data driven anticipation evaluation, user-friendly display, and real-time anomaly detection. This delay prevents seasonal error detection and compromises safety, reliability, and customer experience. The current firm is addressing this limitation by creating a comprehensive software platform that brings together the statistics gathered by the detector and the BMS departments with an intelligent inference and user-friendly image. To actively discriminate and alleviate battery-related hazards: Real-time monitoring, machine learning-based anomaly detection, and exchange of protected facts. The platform is scalable and simple to use thanks to open-source procedures such as Flask for API expansion and Streamlit for front-end image perfection. Moreover, the organization's ability to predict hazardous conditions, such as overheating or other inferno problems, is enhanced by the introduction of automated logic forecasting, which enables timely intervention. The firm focuses on imitation and software-based proof of impression (PoC), using mock datasets and computerized detectors to mimic a real environment. The long-term objective shall be to extend the current organization so as to provide a completely deployable cloud alternative transport solution for the EV manufacturer, scientists, and fleet operator.

1.2 Motivation and Problem statement

As electric vehicles (EVs) become mainstream, demand for safe and extra reliable battery compositions has grown significantly. EVs, however, deal with serious safety concerns, particularly related to battery malfunctions such as overheating, short circuits, and thermal surges which may lead to explosions or other flames, despite their advantages in energy productivity and environmentally friendly effects. Battery management systems (BMS) are usually designed to monitor battery health and performance, although they are usually limited in scope and do not have predictive expertise and comprehensive client interface. The inability to proactively identify the early warning signs of battery failure using real-time statistical analysis and intelligent resolution is one of the main limitations of the new BMS fix. Usually, these systems provide reactive warning rather than predictive warning, which may delay support and compromise safety. Moreover, the absence of a central screen and integration into the system of intelligent devices makes it difficult for users, producers, and experts to monitor and determine.

1.3 Scope and limitations

1.3.1 Scope

- Build a software system to monitor EV battery parameters like SOC,SOH, voltage, and temperature.
- Create a user-friendly dashboard that visualizes all important battery metrics.Connecting AI/ML models via APIs to predict infernal problems

and find anomalies in battery conductivity.

- Provide early warnings when abnormal patterns or potential fire conditions are detected.
- Use simulated sensor data and open-source datasets for testing without needing physical EV hardware.

1.3.2 Limitations

- The system is tested only with simulated data, so its real-world performance may differ.
- Predictive and anomaly detection may never be perfected, provided the data set doesn't shields all real scenarios.
- Handling large EV fleets or cloud-level deployment may need further improvements.

1.4 Relevance and Type

These companies are focusing on the development of the AI-powered EV Battery Flames Prevention System, which does not fall outside the realms of AI, machine learning, IoT monitoring, and battery management. It is an applied research project aimed at improving the way energy vehicle batteries are monitored and maintained safely. By using AI and ML models, the structure can evaluate battery behavior in real time, detect unusual forms, and even predict untimely signs of heat problems before they become dangerous. The current support users, scholars, and manufacturers of EVs produce quick, more light determinations. The platform also emphasizes safe information handling, clear visual display, and simulation testing, making it pragmatic and simple to use.

1.5 Organization of the report

The upcoming sections of this report are organized as follows:

- **Literature Survey** – This section reviews existing research on EV battery monitoring, thermal runaway detection, anomaly prediction, and AI-based safety systems. Each paper is summarized and compared to highlight its relevance to the proposed solution and how this project advances current approaches.
- **System Design and Implementation** – This part explains the overallarchitecture of the platform, including software requirements, functionaland non-functional specifications, module descriptions, API integration,and the complete implementation of the real-time monitoring dashboardand AI prediction system.
- **Results, Conclusion, and Future Enhancements** – This sectionpresents the outcomes of the project, including the system's real-time monitoring performance, anomaly detection results, dashboard function-ality, and security features. It also discusses potential future improve-ments such as integration with real EV hardware, mobile app deploy-ment, and enhanced predictive modeling.
- **References** – A detailed list of all research papers, technical articles,datasets, and online resources used throughout the development of the project.

Chapter 2

Literature Survey

2.1 Article 1: Modeling of the Battery Pack and Battery Management System towards an Integrated Electric Vehicle Application[1]

2.1.1 Brief Findings

The author provides a complete design and simulation model to represent a live vehicle (EV) battery battalion together with its battery management system (BMS). The authors show that the performance of the EV battery cannot be accurately measured using only the cell level model; instead, it is necessary to combine electrical, thermal, and BMS management modeling to obtain a reliable prediction.

The significant penetration lies in the fact that the interaction of the cell movement (voltage drop, inner resistance, thermal rise) and the BMS processes (SOC assessment, cell reconciliation, safety cuts) significantly influences vehicle efficiency and battery health. The analysis confirms that the correctness of the assessment of the state of charge and the temperature monitoring directly influences the second life of the battery battalion, the general use of energy, and the operational reliability of the EV.

The reason is that a model-based BMS outline, together with realistic launch revolutions and a battalion configuration, can retrofit real-world EV performance close enough to support design validation and error prediction without human testing.

2.1.2 Design/Methodology/Techniques

The analysis uses a replica technique using MATLAB/Simulink, where the battery structure is modelled and tested before it is integrated into a complete EV structure. The relevant lithium ion cell shall remain represented by means of an Equivalent Circuit Model, including the new voltage, the intrinsic resistance, and the RC component which changes simultaneously with the temperature in order to reflect the real exile. Then the cells are arranged in a series of parallel lines to form a battery battalion, and thermal communication inside the cells is ensured to increase the temperature and uneven heating. To provide State of Charge assessment, safety monitoring, and cell coordination, a battery direct organization (BMS) model will be added. The SOC shall be premedicated by means of a loanblend method combining Coulomb's count with voltage corrections to improve accuracy. The BMS continuously monitors the voltage, connection, and temperature of the cell within the system in order to detect hazardous environments since the Passive Reconciliation Model ensures the uniformity of the cell voltage. Finally, the battery battalion and the BMS are integrated into a complete energy vehicle model, including the motor, inverter, and real drive, allowing the structure to exist under realistic load conditions such as acceleration, braking, and regenerative charging.

To provide State of Charge assessment, safety monitoring, and cell alignment, a dedicated battery leadership organization (BMS) model will be added. The SOC shall be calculated by a hybrid method combining Coulomb's count with voltage corrections for greater accuracy. The BMS continuously proctors the voltage, current, and temperature to a dangerous state, while the passive corrections structure maintains the cell voltage uniform.

Finally, the battery battalion and the BMS are integrated into a complete energy vehicle model, including the motor, inverter, and real driving sequences, so that the framework can be measured under realistic load conditions such as acceleration, braking, and regenerative charging.

2.1.3 Results Achieved

The results show that the fake BMS maintains strong SOC accuracy, prevents thermal hot spots, and successfully reduces cell imbalance. These improvements together contribute to the second reliability, life expectancy, and overall energy productivity of the battery battalion. The author believes that an integrated replica strategy would be a valuable tool for EV manufacturers and researchers, as long as it reduces the need for material prototypes, accelerates evolution, and ensures better decision-making in the face of untimely design delays.

2.2 Article 2: Monitoring of Thermal Runaway in Commercial Prismatic High-Energy Lithium-Ion Battery Cells via Internal Temperature Sensing[2]

2.2.1 Brief Findings

This research shows that the position of the temperature detector in a large prismatic lithium-ion cell provides a great many former and overshooting of the target warning of thermal runaway compared with the traditional surface detection. The researchers found that the cell's internal temperature rises significantly faster than the covering, particularly during overcharging. Since then, the combined intrinsic detectors detect the peak of the no tax return era, a golden age for BMS safety support. The work also demonstrated that it was technically feasible to connect a thermocouple to a cell of high energy (95 Ah) with no damage to its electrochemical deportment, an open door to a protected EV battery battalion.

2.2.2 Design/Methodology/Techniques

Scholars first opened a commercial 95 Ah NMC811 prismatic cell in a glovebox and carefully inserted a pair of Type-K thermocouples between two layers of double jelly without damage to the inner layer. The cell shell had been precisely cut, the jelly roll had been unfolded, and a sensor feed hole had been inserted into the thermocouple through the outer layer of the centrifuge parallel to the same height. After the placement of the sensor, the cell was resealed using organizational adhesive, refilled with electrolyte to compensate for vaporization, and tested for leakage. The modified cell then underwent a control charge–discharge cycle to check that detector interpolation does not alter the normal performance. Finally, a simultaneous overcharge trial of a modified cell and an identical mention cell was performed in a thermally controlled abuse test chamber, where the temperature, voltage, and gas vent temperature were monitored to determine the onset and progression of thermal runaway.

2.2.3 Results Achieved

The investigative creation that integrated the thermocouple possessed practically no pessimistic ramification over the cell's capacity or electric resistance, verifying the safety of the transformation. Internal temperatures were consistently higher than skin temperatures during normal cycles, confirming the requirement for internal detection. While overcharge-induced thermal runaway, intrinsic detectors detect the crucial runaway-trigger temperature (T2) 21 second former compared to veneer sensors, a significant advance in timely warning. The fact that the temperature inside exceeds 900 °C and the facade temperature is significantly lower demonstrates the underestimation of the actual cell environment. Overall, the analysis shows that in-cell detection provides earlier, more reliable, and more detailed knowledge of the setback mechanism in the high-energy lithium-ion cell, which is highly regarded as a safer BMS design.

2.3 Article 3: The Impact of a Combined Battery Thermal Management and Safety System Utilizing Polymer Mini-Channel Cold Plates on the Thermal Runaway and Its Propagation[3]

2.3.1 Brief Findings

This study examines whether a lightweight polymer mini-channel cold home plate can simultaneously function as a cooling framework and a safety barrier in a lithium-ion pouche cell battery battalion. The author proposes that these polymer plates, which are placed between adjacent pouch cells, help delay the onset of thermal runaway in the event of severe overcharge and significantly reduce the threat of thermal runaway propagation to adjacent cells. Unlike standard metallic elements cold home plate, these polymer compositions balance heat dissipation with insulation, allowing them to draw heat away under normal/early maltreatment conditions as well as barricade strong heat transport during a catastrophic meltdown. Generally speaking, the sheets show that a properly manufactured polymer mini-channel cold home plate can be used as a combined battery thermal supervision framework (BTMS) and safety safeguard component to provide a lightweight and space-efficient solution for dynamic vehicle battery capacities.

2.3.2 Design/Methodology/Techniques

Scientists have created a polymer cold home plate made of polycarbonate using micromilling and thermal bonding to create a leak proof structure inside the fluid channels. These plates were only 2 millimeter thick and had 24 minichannels intended to distribute the coolant equally so as to maintain systematic robustness and insulation properties. The cooling housing plate has been placed directly between two 12.5 Ah NMC pouches inside a steel compression frame which ensures uniform compactness and excellent Thermal contact.

Thermocouples were placed in a number of positions close to the cell in order to monitor the variations in temperature, and a high-speed camera recorded body movements such as discharges and cell combustion. The test apparatus allowed deionized water at controlled temperatures (5°C, 20°C, 30°C, 40°C) to current via the home plate, while the overcharge cell was driven beyond 200 percent SOC close to 1°C to deliberately cause a thermal runaway. Several experiments were also conducted without thermal conditioning in order to establish a baseline, while another experiment imitates a cooling system failure by increasing the temperature of the coolant inlet or filling the coolant stream.

The author shall measure cell voltage, temperature progression, discharge timing, start of thermal runaway, and whether heat transport led to the ignition of the adjacent cell in an individual trial.

2.3.3 Results Achieved

The baseline experiment confirms that within an hour of overcharging, the uncooled pouch cell enters a complete thermal runaway and transfers enough heat to cause the neighbor cell's ignition within approximately a minute. However, the thermal behaviour of the overcharging cell dramatically changed during the polymer minichannel home plate's operation, and the overcharging cell could not only reach the conditions necessary for thermal overshooting within the usual 1 hour window, even at 1°C overcharging rates. When the coolant inlet temperature was between 5 and 30°C, the external temperature remained far lower—approximately 50–60°C. The current statement says that the home plate removes enough heat to decelerate or otherwise interrupt the chain of the inner chemical reactions chief in order to cause a thermal explosion.

Even below a biased cooling agent malfunction (40°C inlet temperature) or an impermanent loss of overcurrent, the plate delays the progression of thermal runaway and completely prevents its propagation to the adjacent pouch cell. The present illustration shows that the polymer plate provides a combined cooling and thermal barrier protection. The cooling capacity reaches approximately 2.2 kW/m2.

Generally speaking, the results show that the polymer minichannel cold plate, which slows down the premature thermal runaway and prevents heat transport to the neighboring cell, provides a promising combined BTMS+safety solution for the EV pouch cell faculty.

2.4 Article 4: Advances and Challenges in the Battery Thermal Management Systems of Electric Vehicles [4]

2.4.1 Brief Findings

That assesses the research by which the various Battery Thermal Management Systems (BTMS) ensure the safety, productivity, and longevity of the EV battery. It focuses on three main strategies—passive, active, and hybrid cooling—and explains what constitutes individual tactic work, how it works effectively, and what it entails. The author points out that traditional cooling methods are facing significant limitations as battery density increases and demand for fast charging increases. For the upcoming fast trucks, hybrid cooling solutions, improved substances, and sophisticated thermal design are considered to be of great importance.

2.4.2 Design/Methodology/Techniques Adopted

The authors use a systematic literature review method to evaluate and compare a wide range of BTMS technologies based on the heat transfer mechanism, cool substances, and battery battalion arrangements. Passive processes identical to inherent convection, heat conductors, and phase change components are measured for scalability and heat absorption capacity. Active systems, including coerce space cooling and various liquid cooling channel designs, are analyzed using a report model, experimental studies, and performance benchmarks. The critique also includes a comparative assessment of the geometry of the channel, the type of coolant, the fan-assisted airflow design, and the hybrid configuration which combines passive and active elements to optimize thermal stability.

2.4.3 Results Achieved

The appraisal reason is that during passive BTMS, which proposes simplicity and reduced power usage, they cannot meet the demand of high capacity EV battery. Activecooling, especially runny cooling, provides excellent temperature management but requires excessively complex designs, higher cost, and higher energy consumption. Hybrid systems systematically outperform single methods by balancing efficiency, safety, and flexibility, making them the most promising technique for future EV platforms. Furthermore, the report underlines unsolved obstacles such as thermal runaway risks in next generation batteries and the need for light, safer, and faster heat dissipating components.

2.5 Article 5: Battery Thermal Management Systems: Current Status and Design Approach of Cooling Technologies[5]

2.5.1 Brief Findings

The paper provides a detailed description of how the current battery management systems (BMS) ensure safe, efficient, and secure operation of the EV battery. It describes the values of monitoring voltage, temperature, charge, and fitness to prevent failures such as thermal runaway or cell degeneration. The author, in addition to Analogize, centralize, modular, and share a BMS architecture demonstrating the power of a particular design in terms of reliability and scalability. The manuscript stresses the importance of a well-designed BMS as a pillar of EV battery safety and performance.

2.5.2 Design/Methodology/Techniques

The authors adopt a survey-style methodology, systematically evaluating existing BMS architectures, sensing technologies, estimation algorithms, and control strategies based on published research and commercial EV implementations. The review discusses the functional design of BMS hardware—such as sensor networks, microcontrollers, relays, and protection circuits—and analyzes how measurement techniques like voltage sensing, temperature profiling, and current sampling contribute to system accuracy. Advanced estimation techniques, including extended Kalman filters, equivalent-circuit modeling, and machine-learning-based prediction methods, are examined to highlight how they improve SOC, SOH, and thermal-state estimation. The study also reviews safety standards and fault-diagnosis frameworks used to detect abnormal behavior during fast charging, discharging, or extreme environmental conditions.

2.5.3 Results Achieved

The review shows that distributed and modular BMS architectures offer superior scalability and safety compared to traditional centralized systems, especially for large battery packs used in modern EVs. The paper also finds that advanced algorithms significantly improve the accuracy of key battery-state predictions, enabling better energy management and extending battery lifespan. Furthermore, the study highlights that combining robust sensing hardware with intelligent control software greatly reduces failure risks and enhances overall EV performance. However, it also underscores ongoing challenges such as sensor drift, thermal imbalance, increasing data-processing demand, and the need for stronger cybersecurity measures in connected BMS environments.

2.6 Article 6: A Review of Lithium-Ion Battery State of Charge Estimation Methods Based on Machine Learning[6]

2.6.1 Brief Findings

This paper provides a comprehensive review of how machine learning is transforming State of Charge (SOC) estimation for lithium-ion batteries. It highlights the limitations of traditional estimation methods—such as high model complexity, sensitivity to parameter errors, and low adaptability—and explains how machine-learning models overcome these issues by learning complex nonlinear battery behaviors directly from data. The authors also emphasize that high-quality datasets, proper feature engineering, and careful model selection play a crucial role in improving the accuracy and robustness of SOC predictions.

2.6.2 Design/Methodology/Techniques

The examiner shall assess the organization of the SOC during the three major phases of data collection, model selection, and model verification. It is accustomed to datasets (including NASA, CALCE, ADVISOR, and other individuals) and summarises the required preprocessing strategies such as standardization, dimensionality reduction, angle extraction, and smooth. The author classifies the machine learning model as one of the two collectives of the authoritative nervous collaborations (BPNN, RBFNN, ELM, WNN) and deep learning architectures (CNN, RNN, LSTM, GRU). GA, PSO, WOA, and HBA shall advance the debate in respect of the model concerned. They describe how hyperpa-rameter tuning and evaluation approaches identical to MAE, MSE, and RMSE impactfinal SOC precision are described.

2.6.3 Results Achieved

The review concludes that machine-learning-based SOC methods consistently outperform traditional model-based estimators, especially in handling nonlinearities and adapting to real-world driving conditions. Enhanced neural networks and deep-learning models demonstrate strong generalization and high accuracy, often keeping prediction errors within a few percent. The paper also identifies ongoing challenges—such as data quality, model interpretability, and online adaptability—and provides direction for future improvements, ultimately suggesting that intelligent, data-centric SOC estimation is becoming essential for next-generation battery management systems.

2.7 Article 7:Adaptive State-of-Charge Estimation for Li-ion Batteries by Considering Capacity Degradation[7]

2.7.1 Brief Findings

This paper presents an adaptive SOC estimation method that explicitly considers battery capacity degradation, which significantly affects SOC accuracy over time. The authors show that as batteries age, relying on a fixed rated capacity leads to growing estimation errors. Their approach combines an Equivalent Circuit Model (ECM), an adaptive parameter-identification method, and real-time capacity prediction to improve SOC accuracy, even as the battery's characteristics evolve.

2.7.2 Design/Methodology/Techniques

The methodology integrates three key components.A second-order ECM, which models battery voltage dynamics, and a Forgetting-Factor Recursive Least Squares (FFRLS) algorithm for online identification of model parameters that drift due to aging, also an Adaptive Extended Kalman Filter (AEKF) that updates SOC in real time while adjusting for noise variations and changing battery behavior.

Additionally, a degradation-aware capacity prediction model is incorporated to ensure that SOC estimation remains accurate even as usable capacity decreases. The paper also performs a sensitivity analysis showing how capacity errors directly propagate into SOC errors, justifying the need for adaptive capacity tracking.

2.7.3 Results Achieved

The proposed adaptive SOC estimator achieves a maximum SOC error of less than 1.3 percent, demonstrating significant improvement over conventional AEKF methods that assume constant capacity. The integration of real-time capacity updates enhances robustness, reduces cumulative estimation drift, and maintains accuracy under dynamic driving conditions. Overall, the method proves to be reliable, adaptable, and well-suited for electric-vehicle battery management systems where aging effects cannot be ignored.

2.8 Article 8: Hybrid State of Charge Estimation of Lithium-Ion Battery Using the Coulomb Counting Method and an Adaptive Unscented Kalman Filter[8]

2.8.1 Brief Findings

This paper presents a hybrid SOC estimation technique that combines the simplicity of Coulomb Counting with the accuracy of an Adaptive Unscented Kalman Filter (AUKF). The authors emphasize that traditional SOC estimation struggles with nonlinear battery behavior, temperature variations, and degraded battery conditions. By integrating AUKF with optimized battery model parameters (identified using the African Vulture Optimization Algorithm), the method achieves far lower estimation errors than conventional hybrid techniques. The study concludes that this adaptive hybrid method is more robust and accurate across different temperatures, load profiles, and aging conditions.

2.8.2 Design/Methodology/Techniques

The authors model the battery using a single RC branch equivalent circuit including OCV–SOC nonlinear mapping, ohmic resistance, and transient elements.AVOA is used to identify key model parameters such as OCV, R, Rtr, and Ctr under various loading and fading conditions. SOC is then estimated through a two-stage hybrid approach:CCM predicts the initial SOC evolution, while the AUKF corrects it in real time using voltage and current measurements while dynamically adjusting noise statistics. Four case studies (with/without load and aging conditions at different temperatures) are conducted using a 2.6Ah Panasonic Li-ion cell.

2.8.3 Results Achieved

Simulation results show that the proposed hybrid estimator significantly reduces SOC error compared to CCM alone and other Kalman-based combinations (CCM–EKF, CCM–UKF, CCM–AEKF). The method achieves the lowest Integral Square Error (ISE) across all test conditions, demonstrating high accuracy and stability even under nonlinear, noisy, or degraded battery settings. The study concludes that this hybrid method is well suited for practical BMS applications requiring long-term reliability and adaptive behavior.

2.9 Article 9:SOC Estimation with an Adaptive Unscented Kalman Filter Based on Model Parameter Optimization[9]

2.9.1 Brief Findings

This paper focuses on improving SOC estimation accuracy by optimizing battery model parameters and integrating them with an Adaptive Unscented Kalman Filter (AUKF). Through experimental analysis, the authors show that a second-order RC model best captures battery polarization effects compared to single- or multi-order models. By optimizing key model parameters before filtering, the SOC estimation becomes more accurate and stable, especially in dynamic operating conditions. The work highlights the importance of precise model identification before applying advanced filtering algorithms.

2.9.2 Design/Methodology/Techniques

The paper begins by evaluating different equivalent circuit models and identifies the second-order RC model as the most suitable. Terminal voltage response tests and exponential curve fitting are used to validate this choice. Model parameters (R,Rp,Rs,Cp,Cs) are obtained using recursive least squares under dynamic stress testing. This optimized model is then used in an AUKF, which updates covariance values adaptively to better handle real-time noise variations. The authors compare SOC estimation using pre-optimized and post-optimized parameters to quantify the improvement.

2.9.3 Results Achieved

The optimized model combined with AUKF provides consistently more accurate and smoother SOC tracking. The improved AUKF maintains quick convergence of initial SOC errors and reduces overall estimation deviation compared to methods using unoptimized parameters. Simulation experiments show a significant reduction in terminal voltage prediction error, confirming that parameter optimization enhances filter performance without increasing computational burden. This makes the proposed method practical for real-time EV battery management.

2.10 Article 10: State of Charge Estimation of Lithium-Ion Battery Based on Improved Adaptive Unscented Kalman Filter[10]

2.10.1 Brief Findings

This paper proposes an Improved Adaptive Unscented Kalman Filter (IAUKF) to address two major limitations of traditional UKF-based SOC estimation: non-positive error covariance and inaccurate/unknown noise statistics. By combining an improved UKF (based on SVD instead of Cholesky decomposition) with a Sage–Husa adaptive noise estimator, the method enhances stability, prevents filter divergence, and improves SOC accuracy under real driving conditions.The IAUKF demonstrates superior robustness to noise uncertainty and computational errors.

2.10.2 Design/Methodology/Techniques Adopted

The authors select a second-order Thevenin model to capture battery polarization and dynamic behavior. The Ampere-hour method is integrated to define SOC evolution,while the state–space model includes two RC network voltages (Up, Us). Model parameters are identified using recursive least squares, and an OCV–SOC curve is generated through sixth-order polynomial fitting. The IAUKF enhances the UKF by replacing Cholesky decomposition with SVD to maintain positive definiteness of covariance matrices. The Sage–Husa adaptive filter adjusts process and measurement noise online, enabling real-time correction of system uncertainties. The proposed estimator is validated using the Federal Urban Driving Schedule (FUDS).

2.10.3 Results Achieved

Experiments show that the IAUKF delivers higher SOC estimation accuracy, faster convergence, and significantly better numerical stability than the traditional UKF and IUKF. The filter remains stable even under inaccurate noise assumptions and dynamic load profiles. Under the FUDS drive cycle, IAUKF produces the least estimation error, confirming its robustness for real-world EV applications. The study concludes that the IAUKF is highly effective for systems where noise characteristics vary with time and operating conditions.

2.11 Comparison Table

Table 2.1: Comparison of Existing Work and Gap Identification

Project Title and Author	**Problem Addressed**	**Implementation and Results**	**Limitations / Future Scope**
The design of the Battery Pack and Battery Control Structure for a combined electrified vehicle application — Mawuntu et al	Difficulties in accurately modeling the battery battalion and SOC under real driving environments ; need a combined EV + BMS imitation environment.	Developed a complete battery battalion model together with EKF-based SOC evaluation, coolant flow regulation, and passive cell balance. It was integrated with an EV model and tested for four rotations, demonstrating improved SOC accuracy and thermal robustness.	. • Model complexity is high. • Future work includes incorporating SOH prediction and fault detection into the BMS.

Project Title and Author	**Problem Addressed**	**Implementation and Results**	**Limitations / Future Scope**
Monitoring of Thermal Runaway in Commercial Prismatic High-Energy Lithium-Ion Battery Cells via Internal Temperature Sensing — Kisseler et al	Surface sensors detect thermal runaway too late; lack of methods to monitor internal cell temperature in real time.	Inserted two internal thermo couples between prismatic cell jelly-rolls and added surface sensors. Internal sensors detected early temperature rise and the "point-of-no-return" 21 seconds earlier than surface sensors.	• Sensor insertion can alter cell structure; long-term stability requires validation.. • Need scalable, non-intrusive internal sensing methods for commercial EV packs.
Impact of Combined Battery Thermal Management and Safety System Using Polymer Mini-Channel Cold Plates — Graichen et al.	Thermal runaway propagation in battery packs; need for compact cooling solutions that also act as thermal barriers.	Introduced lightweight polymer mini-channel cold plates placed between pouch cells. Overcharging tests showed the system limited peak temperature to 50–60°C, delayed runaway.	• Requires durability testing under vibration and aging. • Fluid leakage and long-term reliability must be addressed.

Project Title and Author	**Problem Addressed**	**Implementation and Results**	**Limitations / Future Scope**
Advances and Challenges in the Battery Thermal Management Systems of Electric Vehicles — Wen et al.	Growing heat loads from fast charging/high-density cells; need to compare passive, active, and hybrid BTMS methods.	Reviewed PCM-based, liquid-cooling, heat-pipe, and hybrid BTMS strategies. Identified that hybrid BTMS offer best performance for modern EV demands. Discussed challenges from solid-state and Li–S batteries.	• Most BTMS concepts are lab-scale; integration challenges (weight, cost, complexity) not fully solved. • Future focus on lightweight materials and fast-charging thermal control.

Project Title and Author	**Problem Addressed**	**Implementation and Results**	**Limitations / Future Scope**
Battery Thermal Management Systems: Current Status and Cooling Technology Design Approaches — Buidin and Mariasiu	Inefficient cooling causes degradation, uneven temperatures, and risk of thermal runaway; need to compare BTMS designs.	Provided design recommendations for cylindrical, prismatic, and pouch cells.	• Few studies consider real-vehicle constraints like vibrations or manufacturability. • Future direction: dynamic BTMS with intelligent control algorithms.

Project Title and Author	**Problem Addressed**	**Implementation and Results**	**Limitations / Future Scope**
A Review of Lithium-Ion Battery SOC Estimation Methods Based on Machine Learning — Zhao et al.	Traditional SOC estimation models struggle with non linearities and require precise modeling; need robust ML/DL-based approaches.	Summarized dataset preparation, ML model selection, and evaluation methods. Compared neural networks, LSTM, CNN, and hybrid models..	• Strong dependency on large datasets; limited real-time validation. • Future research should focus on light-weight ML models optimized for BMS hardware.
Adaptive State-of-Charge Estimation for Lithium-Ion Batteries Considering Capacity Degradation — Xu et al.	SOC estimation becomes inaccurate as batteries age because capacity degradation is ignored.	Used Equivalent Circuit Model + Forgetting-Factor RLS to identify parameters. Added a capacity-degradation prediction model and an Adaptive Extended Kalman Filter.	• Model complexity increases computational load. • Future improvement includes SOC–SOH joint estimation and real-vehicle deployment.

Project Title and Author	**Problem Addressed**	**Implementation and Results**	**Limitations / Future Scope**
Hybrid SOC Estimation Using Coulomb Counting and Adaptive Unscented Kalman Filter — Fahmy et al.	Coulomb counting accumulates large errors; UKF alone struggles with parameter variation and noise uncertainty.	Combined Coulomb counting with Adaptive UKF and used African Vulture Optimizer to tune battery model parameters.	• Requires significant computational resources for optimization. • Future versions should target embedded BMS hardware with reduced complexity.
State Of Charge Estimation with Adaptive UKF Based on Model Parameter Optimization — Guo et al.	Inaccurate RC model parameters cause SOC errors; traditional UKF fails under nonlinear battery conditions.	Developed a second-order RC model; optimized parameters; used Adaptive UKF for online SOC estimation. Optimized model improved accuracy compared to the baseline RC model.	• Limited to specific cell chemistry; testing focused on simulations. • Future work includes extending to high-capacity EV cells and real driving cycles.

Project Title and Author	Problem Addressed	Implementation and Results	Limitations / Future Scope
State Of Charge Estimation of Lithium-Ion Battery Based on Improved Adaptive Unscented Kalman Filter	UKF may fail when noise statistics are inaccurate; error covariance becomes non-positive, reducing accuracy.	Proposed IAUKF combining Improved UKF + Sage-Husa adaptive filter to stabilize covariance and adaptively correct noise statistics. Testing under urban driving cycles showed higher accuracy and stability than standard UKF/IUKF.	• Algorithm complexity is high; hardware implementation for real EV BMS is challenging. • Future work needs real-vehicle testing and computational optimization.

2.12 Summary

This section reviews ten studies on lithium-ion battery safety, thermal monitoring, SOC estimation, and early fault detection. The studies point out key challenges such as thermal runaway, inaccurate SOC values and limited surface monitoring. To address these issues, researchers suggest solutions like internal temperature sensing, improved thermal management systems, hybrid cooling methods, AI-based SOC estimation.

The next section presents the design of an intelligent EV Battery Fire Prevention System that uses multi-sensor data, MQTT communication, AI-based anomaly detection, and user alerts to improve battery safety and reliable vehicle operation.

Chapter 3

Software Requirements Specification

3.1 Functional requirements

The main function of the software shall be to gather live battery information, process it intelligently, and inform the user of any potential safety problems. The framework continuously receives sensor readings from faculty identical to ACS712 and WCS1500, INA219 for voltage and influence monitoring, DS18B20 for temperature monitoring, and GPS for battery location. In addition, these detectors are connected to an ESP32 accountant which acts as a bridge between the hardware model and the backend software.

Once the information has reached the backend, the software processes it to calculate essential parameters such as voltage, current, temperature, charge statement, and health. A combined machine learning model, which checks for unusual forms, such as sudden increases in temperature or unexpected increases in temperature, then analyses these standards. The structure predicts the possibility of thermal escape or combustion risk and communicates the undesirableness at levels such as Normal, Warning, or Critical if the anomaly is detected.

To help the consumer understand what is happening inside the battery, a real-time monitoring board using Streamlit visualizes each reading as it arrives. The display shows graphs, colored warnings, old biases, and even the geographic location of the battery using GPS data. The display immediately underlines the subject and gives a warning that appropriate action may be needed in the event of abnormal behavior.

In addition to publishing live statistics, the backend software shop checks each and every detector in the database. The present ancient facts are becoming useful for trend analysis, performance assessment, and retraining the AI model to improve accuracy beyond the era. In addition to the constant monitoring cringle, the architecture also includes a dedicated backend faculty responsible for data access, storage, model inference, and exchange with the splash screen via APIs.

3.2 Non-Functional requirements

In order to ensure safety, reliability, and efficient performance, the smart technology-driven EV Battery inferno prevention framework must meet a number of non-functional requirements. The organization should work in real time, detecting temperature, voltage, and present with very little rotational latency, ideally under a couple of seconds, while the AI model must detect anomalies and emit an alert indoors within a few seconds of recognizing an abnormal form. In order to ensure precise monitoring, a solution must be highly reliable, with near minimum 99 percent uptime during vehicle operation, and sensor readings must be precise within that range. It is also essential to ensure that the MQTT interaction is safeguarded through appropriate authentication and optional encoding during access to the mailable application and that the backend information is restricted so that the user is only authorized. The organization must be scalable, enabling further detection of a fresh automated reasoning model free from major hardware modifications, and the cloud platform must be able to process live streaming data simultaneously from different cars. The software for the ESP32, the machine intelligence model, and the portable use should be modular and simple to update, as well as the sensor calibration settings, which can be changed if necessary. Serviceability is essential, so the portable app must have modern intelligence in a clear and intuitive interface, highlighting the significant battery life and alert status in a simple layout. It is also important to be able to carry them; therefore, the system should work smoothly with different Android versions and be compatible with multiple EV battery configurations. The safety conditions require immediate presentation when the essential battery thresholds, such as overheating, overvoltage, or otherwise abnormal current, are exceeded so that the customer receives clear warning during the promise of fire hazard. Finally, the organization must be certain of the ethics of the facts, minimize the loss of statistics during the transmission, and ensure that each stored copy is perfectly and unaltered, while maintaining the compatibility of the multiple MQTT agents and the BMS architecture.

3.2.1 Safety Requirements

- The system should keep all battery and GPS data safe so that no one misuses sensitive information.
- Any communication between the sensors, ESP32, backend, or dashboard should be encrypted to prevent data leaks.
- Only authorized users should be allowed to access the backend or view system controls.
- The system should regularly back up its data so that everything can be restored easily if something goes wrong.

3.3 User interface design

- The dashboard is designed to be simple, clear, and easy for anyone to understand.
- GPS tracking is included to show the battery's live location in an easy-to-read format.
- The system displays fire-risk predictions clearly so users can quickly spot any dangers.
- Alerts are highlighted prominently so abnormal behavior is noticed immediately.

3.4 Hardware and Software requirements

Hardware Requirements:

- The system uses an ESP32-WROOM microcontroller to collect and send sensor data.
- In order to monitor new, voltage, temperature, and location, they are familiar with detectors such as ACS712, WCS1500, INA219, DS18B20, and GPS faculty.
- In order to operate the display, backstage waiter, and AI model during the show, a normal computer or laptop is sufficient.

Software Requirements:

- The backend is built using Flask or FastAPI to handle APIs and communication.
- The dashboard is created using Streamlit, making it easy to visualize battery data in real time.
- A database such as MongoDB or PostgreSQL is used to store sensor readings and prediction logs. like Proteus or Arduino IDE help simulate the hardware and ESP32 behavior.
- Python is the main language for data processing, prediction, and backend logic.

3.5 Summary

In drumhead, the intelligent technology-driven EV Battery Flames Prevention System was designed to monitor the EV battery in real time, identify potential safety threats, and provide clear, actionable understanding through the synergiestack. In order to create a safe, reliable, and simple platform, it brings together IoT facts, machine learning, and intuitive visuals. Although the new system is simulation-based, it provides a strong basis for future integration with real EV hardware and trade deployment.

Chapter 4

System Design

4.1 Abstract Design

4.1.1 Architectural diagram

Architecture diagram is supposed to give us a blueprint of how the system was constructed. Below is the architectural diagram of how we built our system.

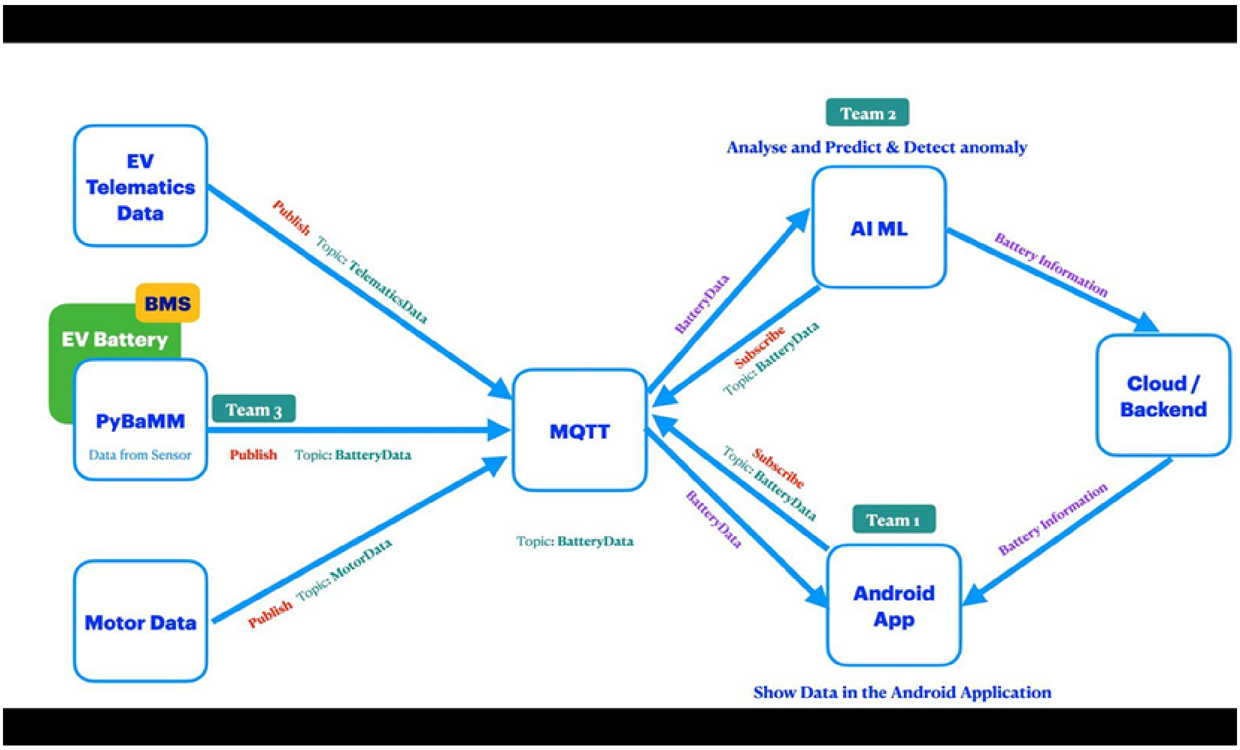


Figure 4.1: Architecture diagram

Using a detector and a BMS to collect structure, battery, motor, and technical data. Any existing knowledge to be sent to the MQTT agent which acts as the central exchange hub. From now on, the AI/ML staff reads the battery facts to evaluate it and detects any abnormality that might indicate a flame hazard. The Android application will also receive and display real-time battery status for the customer during the same period. The processed results are stored in a cloud backend which records the log and provides additional computational analysis. This device ensures constant monitoring, timely detection of fire hazards, and instantaneous reporting to the customer.

4.2 Functional Design

4.2.1 Modular design diagram

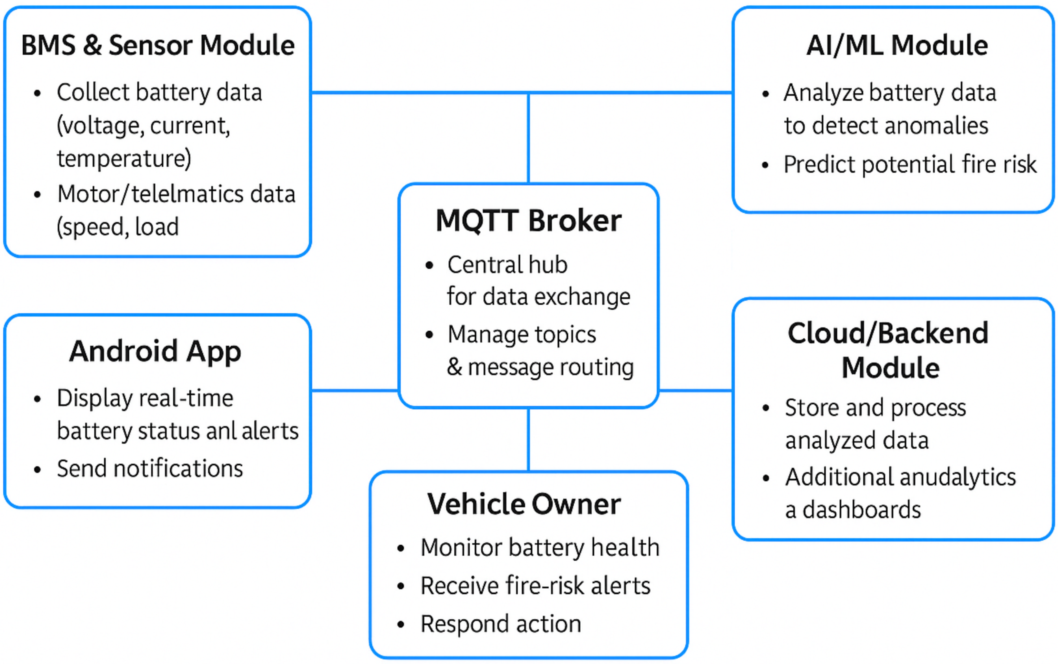


Figure 4.2: Modular design diagram

Modular Design diagram represents a software system in terms of in dependent modules. Each module depicts a functionality of a particular component of the system.

- BMS and Sensor Module

  All hardware components, such as the temperature detector DS18B20, the prevailing detector ACS712/INA219, the voltage sensing circuit, and the telematics data, are included in this faculty. It collects real-time battery health data, including voltage, relevant, temperature, speed, and load. The ESP32 will process the facts and prepare them for transmission.

- AI/ML Module

  The faculty uses a machine learning model to examine the form. It predicts untimely signs of thermal exothermics, overheating, overcurrent, or otherwise abnormal voltage variations. If a dangerous form is detected, it generates an alert and sends its support via MQTT or directly to the cloud.

- MQTT Broker

  MQTT acts as a basic networking hub. The entire Faculty Print else subscribe to the subject BatteryData, Motor Data, and Alert. The agent transmits statistics to the detector, the automated reasoning organization, the cloud, and the mail app. It ensures light, fast, real-time data transmission throughout the system.

- Cloud/Backend Module

  The current faculty shop overall detector statistics, automated reasoning results, and alert log. It performs sustained inference, generates a graph, and relays information to the splashboard. Old studies, model progress, and user reports are also possible in the backend. It can be applied to AWS, Firebase or, alternatively, to each waiter.

- Android App

  Transportable application functions as user interface. It displays real-time battery condition, temperature, voltage, up-to-date and fire-risk warning. It also shows the location and presentation of artificial intelligence. The present Regulation allows the EV owner to take immediate action if the organization detects hazardous activities.

- Vehicle Owner

  That block represents the organisation's final user. The owner will receive a live alert, proctor battery health, and react to the risks. They can see the status of the condition, accept its presence, and follow the recommended safety measures (such as stopping the vehicle if the temperature is detected).

4.2.2 Sequence diagram

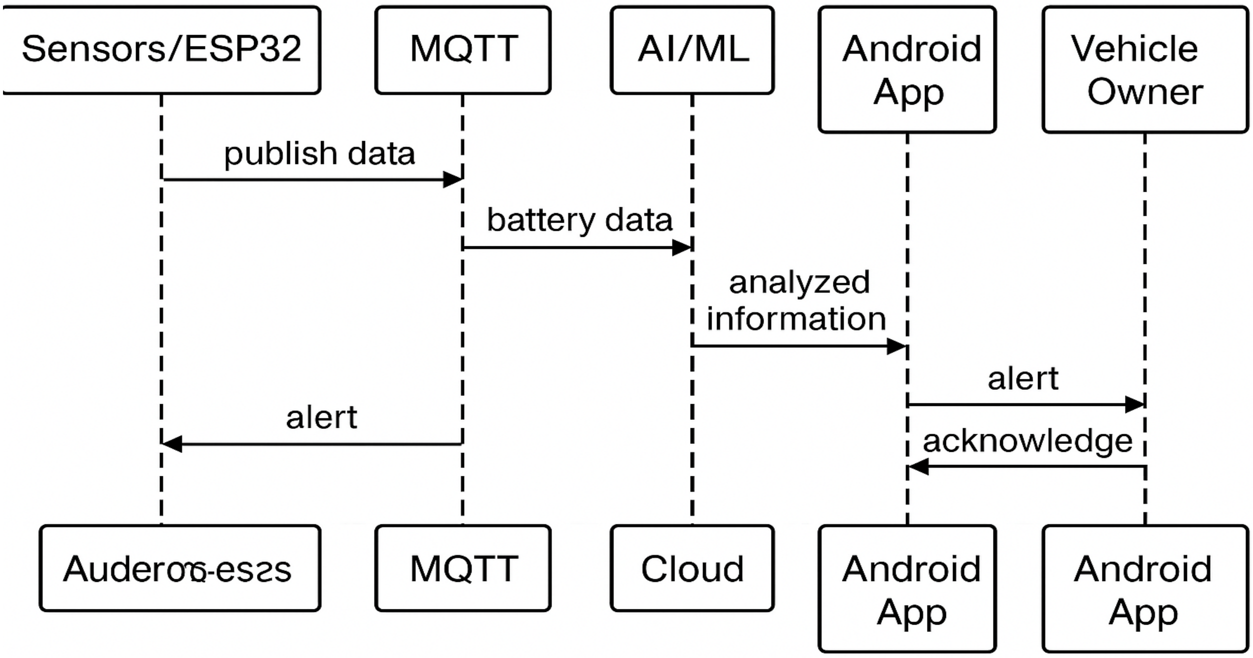


Figure 4.3: Sequence diagram

Sequential diagram helps us understand how different objects interact in a sequential order.

The sequence diagram illustrates the way the EV Battery Flame Prevention System works from the collection of information to the presentation of the customer. The procedure shall be completed together with the detector connected to the ESP32, which continuously measures the parameters of the battery, such as temperature, voltage, current, and location of the GPS. The ESP32 then prints this information to the MQTT Agent, which acts as the focal point of communication. The AI/ML Faculty subscribes to the battery data subject and receives the reading from the entrance detector. It analyses the facts of the real era in search of anomalies such as overheating, abnormal currents, or signs of thermal detonation in advance. If each liability is identified, the machine intelligence faculty prints an alert message for the MQTT agent. In addition to storing analyzed facts for logs and upcoming model training, the cloud backend can. In the meantime, using Android, which has been added to the list of alert subjects, immediately receives the printed message and presents a gift to the driver. Once the owner sees the warning, he accepts it via the app and completes the procedure. The current flow aims at continuous monitoring, swift detection of hazardous situations, and immediate user comprehension.

4.2.3 Use case diagram

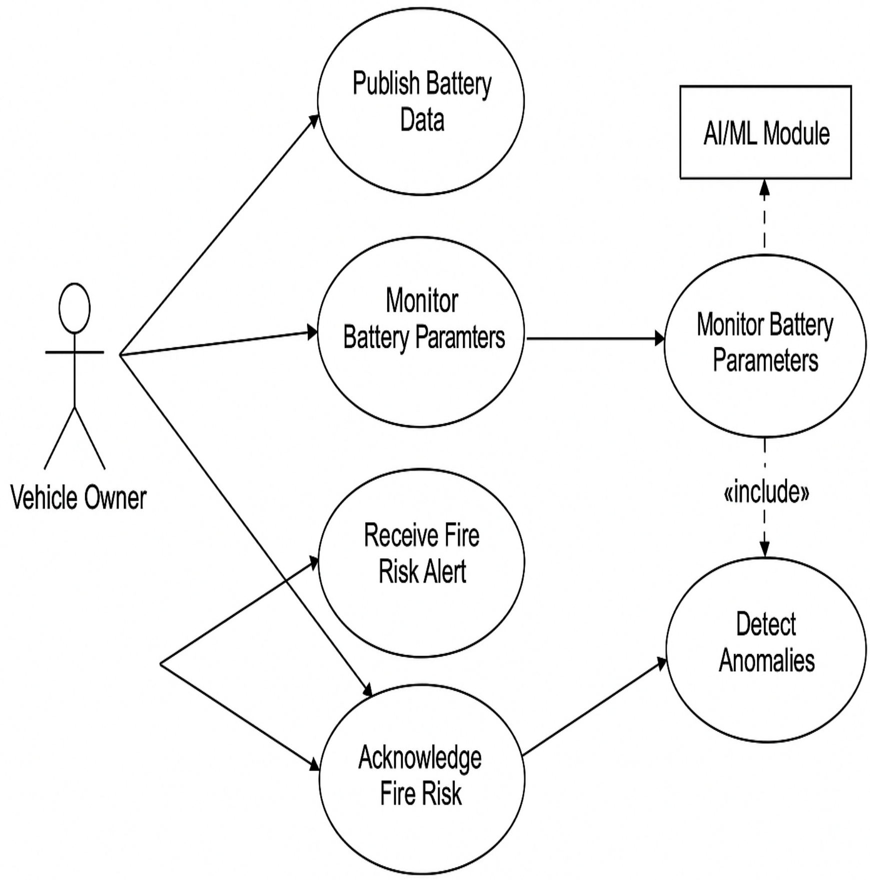


Figure 4.4: Use case diagram

Use Case diagram is supposed to represent the interactions between the different actors and the system. Here, the User interacts with the system through:

- Vehicle Owner checks battery health and receives alerts.
- ESP32/Sensors publish battery data (temperature, voltage, current) to the system.
- AI/ML Module analyzes this data to detect any fire-risk or abnormal patterns.
- If danger is found, the AI sends an alert.
- The Android App receives the alert and shows it to the owner.
- The Owner acknowledges the alert on the app.

4.3 Control Flow Design

4.3.1 Activity diagram for use cases

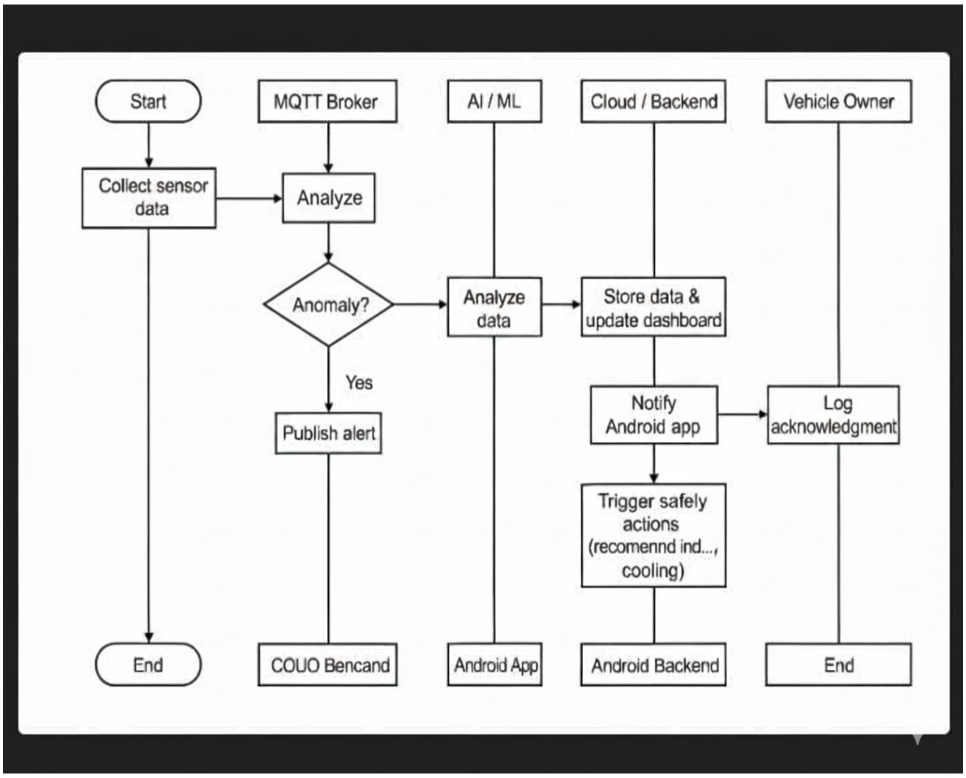


Figure 4.5: Activity diagram

An Activity Diagram represents the sequence of operations and workflow within the system.
The project diagram shows the running time of the EV Battery Flames Prevention Structure detector (ESP32/BMS), gathering battery and telematics information and printing it for the MQTT Agent. The AI/ML faculty subscribes to this information and analyses it for anomalies. If no anomaly is found, facts shall be recorded, and the framework shall continue to be monitored. If an anomaly is detected, an alert is printed, and the cloud/backend archives the incident, updates the splash screen, and informs the Android application. The app transmits the warning to the driver of the vehicle, who can accept it; the cloud records the admission, and the structure, possibly, recommends safety measures (reducing charges, facilitating cooling, recommending safe completion). Then he'll draw it on the screen.

4.3.2 Summary

In this chapter, we went through all kinds of diagrams that help us better understand the system that we built and also help the reader understand what we brainstormed while building this system.

Chapter 5

Implementation

5.1 Software Implementation

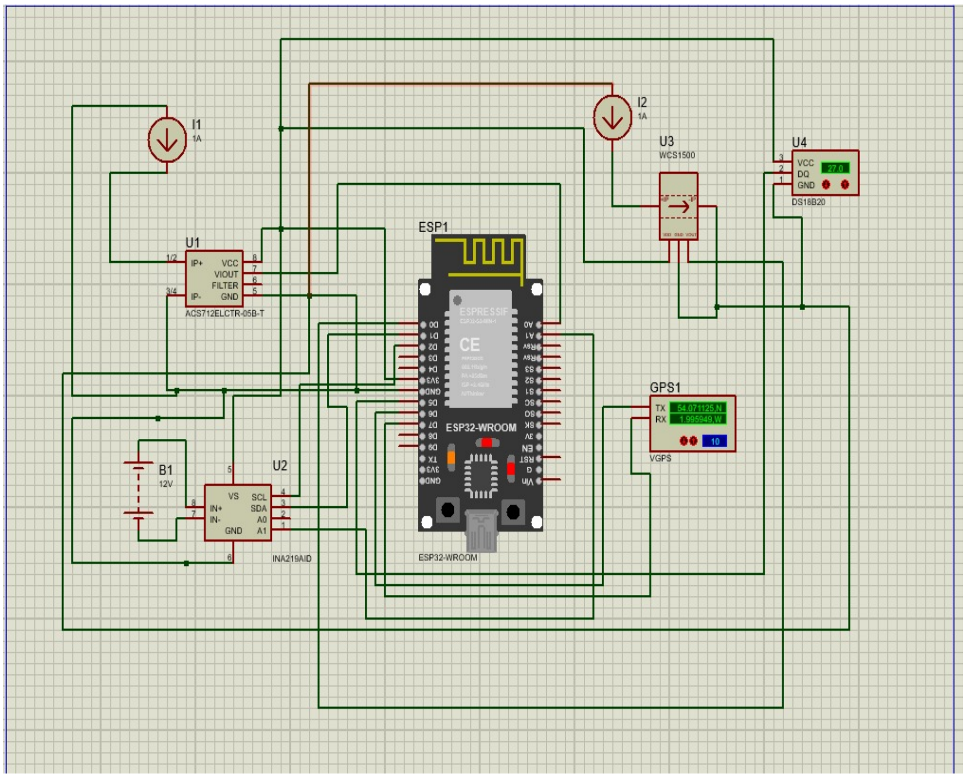


Figure 5.1: Circuit diagram

The circuit diagram shows the complete hardware equipment used to sense the critical EV battery parameters and transmit them to the ESP32 for real-time monitoring. The ESP32 microcontroller is a basic measurement processing unit that receives inputs from various detectors. In order to measure the second voltage and load relevant to the battery, the INA219 voltage and the new detector shall be connected to the I2C interface, while the ACS712 and

WCS1500 new detectors shall monitor the movement of the motor and the high current in order to locate the abnormal surge. In order to continuously monitor the battery temperature, to help detect overheating or thermal runaway environments in advance, a DS18B20 temperature detector shall be fitted. A GPS faculty interfaced via UART provides a real-time location of the vehicle, which becomes a critical firehazard alert at the moment. A 12V battery pack which distributes its influence to the detector and ESP32 via a control cable drives the entire apparatus. Each detector's end product is sent to the ESP32, which measures the collected data and transmits them back to the mainframe via MQTT for further AI evaluation and user notification. The combined circuit ensures the continuous monitoring of the voltage, current, temperature, and location of the EV battery, which constitutes the cornerstone of the EV battery fire prevention system.

5.2 Hardware Implementation

The hardware implementation consists of the ESP32 microcontroller, which functions as the basic unit of measurement for the roll-up and handling detection facts. The company uses a INA219 detector to measure battery voltage and current, ACS712 and WCS1500 detectors to monitor motor and high current current, and a DS18B20 detector to monitor battery temperature. Additionally, a GPS faculty may be connected to provide real-time vehicle location. All these detectors communicate with the ESP32 via analogue pin, I2C, UART, or any other single wire protocol. The circuit is powered by a 12V battery which supplies the detector and ESP32 with safe operating voltage via a regulator. The microcontroller reads all the detectors, performs basic filtering, and transmits the processed data to the cloud using the MQTT protocol. The hardware device enables the continuous monitoring of the critical battery parameters, which requires the quick detection of the fire hazard.

5.3 Summary

In order to measure battery voltage, current, temperature, and situation in real time, the hardware uses a ESP32 link to the detectors INA219, ACS712/ WCS1500, DS18B20, and a GPS module. Send relevant information via MQTT. The software reads the standards for the detectors, the procedures attached to the ESP32, and transmits them to the AI/ML model, which analyses the data in the event of a fire hazard. The cloud shop alert, and the Android app give real-time location and warning to the driver. In cooperation with hardware and software, they analyze them together to alert the customer to the risk of battery heat.

Chapter 6

Results

6.1 Results

The model generates detailed battery and vehicle telemetry, including temperature, current, voltage, motor information, speed, and GPS coordinates at the bottom of the transformation in the operating assertion. The results show that the model accurately captures realistic variations in battery performance, such as changes in SOC, motor temperature, and related spikes.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
1	created_at	entry_id	temper	humidity	current	dc voltage	power	ck_voltage	ck_current	ck_power_	oC_percen	oH_percen	ttery_temp	balance_s	motor_rpm	otor_temp	tor_curren	torque_Nm	rge_curren	rge_voltag	rging_tim	peed_kmh	gps_lat	gps_lon	bient_temp_C
2	2025-11-1	40	2.70044	10.50439			0	338.32	45.7	15461.22	28.08	89.64	42.25	balanced	8306	54.85	67.66	188.55	0	390.93	521	0	12.91672	77.62166	18.98
3	2025-11-1	41	2.69158	10.41575			0	387	-181.14	-70101.2	45.01	95.33	31.81	balanced	1647	79.37	-67.57	144.83	46.14	552.97	3509	45.36	13.00673	77.59756	22.92
4	2025-11-1	42	2.67868	10.28681			0	440.94	9.79	4316.8	29.71	94.77	44.19	balanced	4060	69.67	79.07	169.25	20.99	399.43	17505	69.65	12.95817	77.64736	34.32
5	2025-11-1	43	2.66176	10.11758			0	215.55	67.14	14472.03	25.3	96.32	40.96	balanced	59	49.75	154.02	156.85	80.53	340.82	7543	0	12.98208	77.59245	32.09
6	2025-11-1	44	2.67062	10.20623			0	342.14	19.57	6695.68	57.26	95.2	18.65	balanced	1798	42.45	227.69	70.91	32.65	374.75	3462	17.69	12.97016	77.5861	25.53
7	2025-11-1	45	2.66418	10.14176			0	378.44	1.8	681.19	59.95	94.57	44.9	balanced	4578	76.61	-124.26	248.22	52.33	523.29	16462	39.26	12.94505	77.6681	5.54
8	2025-11-1	46	2.68996	10.39963			0	372.47	10.29	3832.72	34.22	92.36	32.62	imbalanc	3500	54.8	-152.07	237.15	0	478.68	17999	42.6	12.89811	77.64953	21.76
9	2025-11-1	47	2.43451	7.84505			0	431.91	40.73	17591.69	4.61	92.93	30.49	balanced	301	37.68	-123.52	91.43	27.64	411.46	14938	45.96	12.92699	77.49744	29.6
10	2025-11-1	48	2.41516	7.65165			0	300.82	23.46	7057.24	61.23	95.71	30.04	balanced	2753	57.2	-37.76	196.94	26.43	341.08	1887	28.78	12.87357	77.65274	27.97
11	2025-11-1	49	2.42161	7.71612			0	282.45	-122.61	-34631.2	65.69	100	30.82	balanced	5112	52.93	-48.45	84.12	0	324.8	17867	84.3	13.03726	77.53059	40.81
12	2025-11-1	50	2.43531	7.85311			0	393.48	115.29	45364.31	58.62	96.51	39.48	balanced	5640	80.64	-77.92	97.7	76.8	420.47	14130	31.98	12.96799	77.6533	27.03
13	2025-11-1	51	2.41436	7.64359			0	455.75	12.47	5683.2	47.97	96.7	42.25	balanced	658	55.97	208.23	173.04	65.64	401.52	3225	0	12.93757	77.62055	18.4
14	2025-11-1	52	2.43451	7.84505			0	447.48	-157.31	-70393.1	18.97	94.84	40.77	balanced	6411	88.48	30.4	184.71	88.51	333.71	7424	78.28	13.0219	77.62355	8.71
15	2025-11-1	53	2.45788	8.07876			0	376.37	-8.98	-3379.8	40.25	92.85	43.65	balanced	2630	75.86	87.53	163.08	54.8	486.69	14235	54.65	12.93911	77.54983	40.91
16	2025-11-1	54	2.41678	7.66777			0	315.46	-202.88	-64000.5	48.11	96.41	42.96	balanced	2684	49.94	158.1	161.56	0	395.6	12721	62.2	12.9551	77.57871	24.01
17	2025-11-1	55	2.41355	7.63553			0	337.88	-28.83	-9741.08	11.98	94.9	43.02	unknown	8648	58.55	96.15	214.78	5.59	572.27	5051	83.86	12.90621	77.53509	18.47
18	2025-11-1	56	2.44095	7.90952			0	488.36	51.65	25223.79	40.58	93.66	44.63	balanced	0	47.6	-135.82	209.69	32.55	443.51	12513	32.09	12.96706	77.62478	28.78
19	2025-11-1	57	2.43612	7.86117			0	337.77	-63.04	-21293	17.83	100	40.73	balanced	4661	56.07	24.25	250.42	42.65	376.47	11794	28.01	12.99943	77.61879	30.18
20	2025-11-1	58	2.41275	7.62747			0	312.6	15.4	4814.04	80.83	99.06	33.43	balanced	2600	46.27	-69.99	118.5	56.74	378.72	19476	15.25	12.99156	77.56066	26.84
21	2025-11-1	59	2.43209	7.82088			0	302.34	25.97	7851.77	94.97	95.89	54.89	imbalanc	5148	62.4	196.06	65.31	61.81	444.44	1650	43.28	13.02383	77.58254	33.34
22	2025-11-1	60	2.41033	7.6033			0	438.86	1.69	741.67	23.66	90.9	33.15	balanced	1466	59.66	22.27	55.81	66.78	372.85	7085	35.57	13.02091	77.58564	29.31
23	2025-11-1	61	2.41839	7.68388			0	475.07	6.72	3192.47	99.85	92.47	34.3	balanced	3585	58.78	-12.7	86.34	39.28	354.85	2739	83.62	13.01596	77.55034	40.53
24	2025-11-1	62	2.41678	7.66777			0	522.46	-35.64	-18620.5	67.84	92.7	47.23	imbalanc	3436	77.89	0.41	251.76	0	411.48	19987	4.38	13.06102	77.61628	29.49
25	2025-11-1	63	2.41597	7.65971			0	442.9	116.1	51420.69	47.87	98.78	27.18	balanced	4419	65.28	211.16	65.67	38.72	401.09	18121	56.99	12.92487	77.61125	8.15
26	2025-11-1	64	2.42725	7.77253			0	425.3	15.45	6570.88	71.93	99.1	38.2	unknown	2303	62.73	57.66	22.09	39.09	539.43	18573	14.77	12.93621	77.64343	24.88
27	2025-11-1	65	2.43692	7.86923			0	442.48	-68.91	-30491.3	30.51	99.09	34.12	balanced	6865	73.05	-16.77	129.48	123.34	558.76	13035	15.52	12.92236	77.53532	37.41
28	2025-11-1	66	2.41436	7.64359			0	251.26	50.05	12575.56	42.14	92.99	36.62	imbalanc	6508	58.46	-54.1	226.41	30.42	433.72	13442	46.29	12.98466	77.68189	33.59
29	2025-11-1	67	2.41355	7.63553			0	478.13	35.52	16983.18	67.54	91.43	42.83	balanced	2708	99.72	-114.47	194.4	59.09	429.11	12361	47.04	12.92514	77.65585	26.17
30	2025-11-1	68	2.42	7.7			0	339.27	-60.63	-20569.9	52.48	93.45	19.59	balanced	6819	58.07	-27.63	213.97	0	412.82	6779	0	13.06448	77.59479	10.34
31	2025-11-1	69	2.42	7.7			0	357.73	51.98	18594.81	65.49	96.65	33.34	balanced	2329	58.27	43.94	301.61	66.62	411.45	4040	52.4	13.0868	77.57698	14.11
32	2025-11-1	70	2.41194	7.61941			0	356.32	-104.67	-37296	76.02	98.88	34.78	balanced	6961	48.33	-179.2	135.41	80.36	259.51	17744	48.86	12.9016	77.61522	16.8
33	2025-11-1	71	2.42645	7.76447			0	428.97	23.24	9969.26	52.75	95.45	40.89	balanced	2990	60.73	103.79	80.6	1.27	342.13	10188	25.83	12.94016	77.59982	30.63

Figure 6.1: Result

6.2 Summary

A battery explosion prevention structure developed in the present undertaking provides a complete and intelligent solution to predict and prevent the risk of a battery explosion in electric vehicles. The structure continuously accumulates real-time battery and telecom statistics by integrating the temperature, current, voltage, and motor load detectors of the ESP32 microcontroller. The existing knowledge will be transmitted by MQTT to an AI/ML model which analyses their shape and detects seasonal warning signs such as overheating, rapid temperature increase, abnormal current spike, or voltage abnormality. The cloud backend server sends an instantaneous message to the driver of the vehicle, enabling timely action and buyer safety. Generally, the enterprise is represented by the way IoT, machine learning, and implant electronics can be used together to enhance a modern battery safety mechanism. The architecture must be scalable, precise, and capable of real-time monitoring, making a valuable contribution towards the evolution of energy vehicle safety and reliability.

Chapter 7

Conclusions and Future work

A complete real-time monitoring solution capable of detecting the early signs of thermal uncertainty in dynamic vehicle batteries has been demonstrated by the EV battery flame prevention framework driven by smart technology. The organization will continuously monitor temperature, voltage, new and vehicle location using MQTT as a study tool by integrating a significant detector into the ESP32 microcontroller. In addition, the AI/ML faculty enhances safety by detecting abnormal paths such as overheating, rapid temperature increases, or overcurrent conditions before they intensify into thermal explosions. By using Android usage, users accept instantaneous alerts to take timely action and avoid hazardous situations. An effective, reliable, and alert safety mechanism is ensured by combining hardware detection, intelligent connection, cloud storage, and AI-driven prediction. The present projects show how IoT and machine learning can significantly improve the safety of EV batteries and user knowledge.

Although the framework is very effective in identifying fire-hazard situations, the area nearby has significant potential for further development. For electrolyte escape or electrolyte discharge, which usually occurs prior to thermal runaway, the upcoming version may include a gas detector (CO2, H2, VOC). The accuracy of the measurement would be increased by adding a cell thermocouple, strain detector, or fiberoptic intrinsic temperature detector. Furthermore, the framework can integrate CAN bus integration to communicate directly with the vehicle's onboard structures and automatically lower the motor load or stop charging in the event of an error. The use of margin ai on the

ESP32 or the use of an excessively powerful accountant would have allowed a quicker local forecast without the reliance of the cloud or the outside observer. Predictive medicine, battery health marking, trip analysis, and service center connection can also be expanded by the handheld application. In the end, the framework could be expanded to a commercial EV safety academy that integrates seamlessly with the latest electric vehicles, together with improved hardware and rigorous testing.

References

[1] Hend M Fahmy et al. “Hybrid state of charge estimation of lithium-ion battery using the coulomb counting method and an adaptive unscented kalman filter”. In: *Energies* 16.14 (2023), p. 5558.

[2] Henrik-Christian Graichen et al. “The impact of a combined battery thermal management and safety system utilizing polymer mini-channel cold plates on the thermal runaway and its propagation”. In: *Batteries* 10.1 (2023), p. 1.

[3] Xiangwei Guo et al. “SOC estimation with an adaptive unscented Kalman filter based on model parameter optimization”. In: *Applied Sciences* 9.19 (2019), p. 4177.

[4] Nadya Novarizka Mawuntu et al. “Modeling of the battery pack and battery management system towards an integrated electric vehicle application”. In: *Energies* 16.20 (2023), p. 7165.

[5] K Dhananjay Rao et al. “A critical review on lithium ion battery modeling, battery management system and thermal runaway issues”. In: *Electrical Engineering* (2025), pp. 1–37.

[6] Juntao Wang et al. “State of charge estimation for lithium-ion battery based on improved online parameters identification and adaptive square root unscented Kalman filter”. In: *Journal of Energy Storage* 77 (2024), p. 109977.

[7] Tianze Wen et al. “Advances and Challenges in the Battery Thermal Management Systems of Electric Vehicles”. In: *Materials* 18.20 (2025), p. 4718.

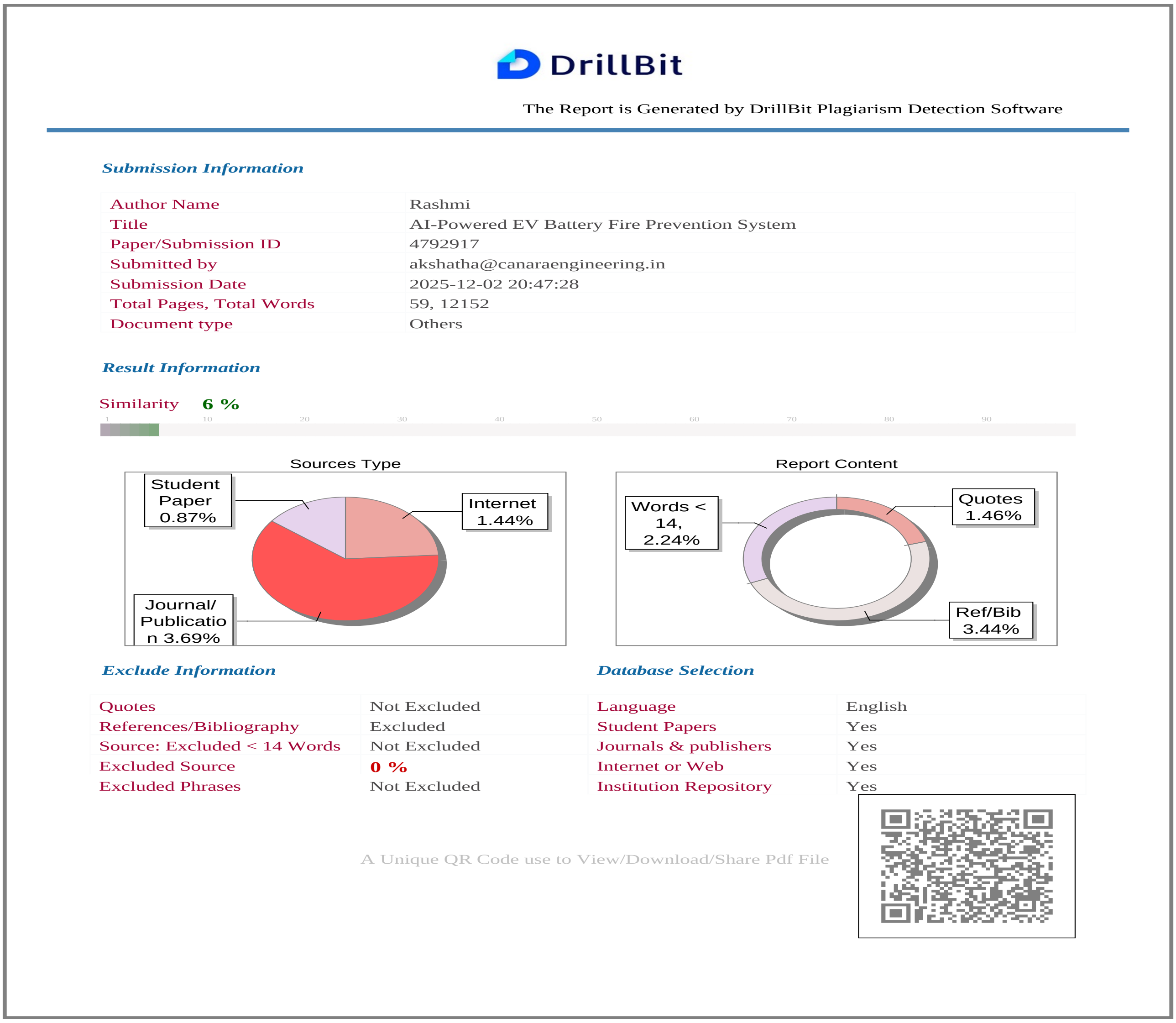
[8] Tianze Wen et al. “Advances and Challenges in the Battery Thermal Management Systems of Electric Vehicles”. In: *Materials* 18.20 (2025), p. 4718.

[9] Peipei Xu et al. “Adaptive state-of-charge estimation for lithium-ion batteries by considering capacity degradation”. In: *Electronics* 10.2 (2021), p. 122.

[10] Feng Zhao, Yun Guo, and Baoming Chen. “A review of lithium-ion battery state of charge estimation methods based on machine learning”. In: *World Electric Vehicle Journal* 15.4 (2024), p. 131.

Appendix A

Drill-bit Plagiarism Report



DrillBit

The Report is Generated by DrillBit Plagiarism Detection Software

Submission Information

Author Name	Rashmi
Title	AI-Powered EV Battery Fire Prevention System
Paper/Submission ID	4792917
Submitted by	akshatha@canaraengineering.in
Submission Date	2025-12-02 20:47:28
Total Pages, Total Words	59, 12152
Document type	Others

Result Information

Similarity **6 %**

Exclude Information

Quotes	Not Excluded
References/Bibliography	Excluded
Source: Excluded < 14 Words	Not Excluded
Excluded Source	**0 %**
Excluded Phrases	Not Excluded

Database Selection

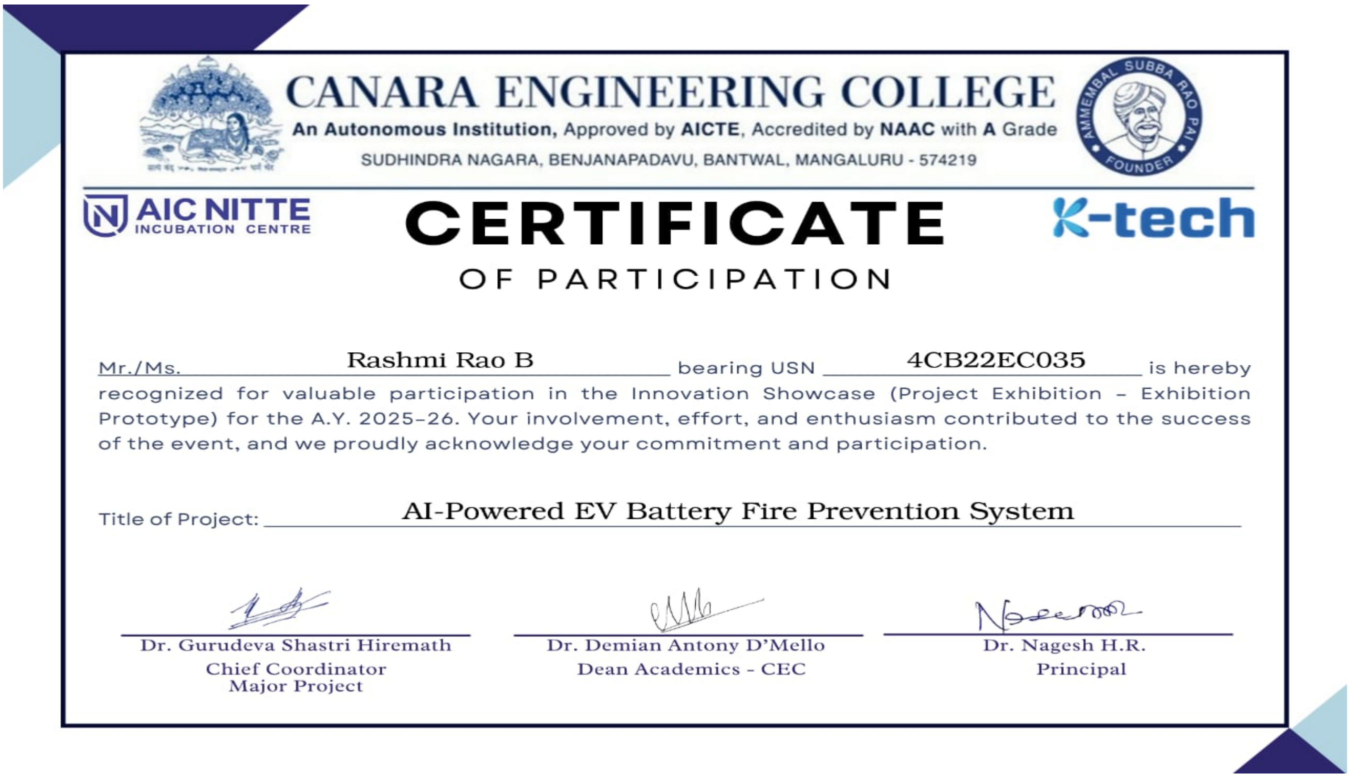
Language	English
Student Papers	Yes
Journals & publishers	Yes
Internet or Web	Yes
Institution Repository	Yes

A Unique QR Code use to View/Download/Share Pdf File

Figure A.1: Drill-bit Plagiarism Report

Appendix B

Project-Expo Details



CANARA ENGINEERING COLLEGE

An Autonomous Institution, Approved by AICTE, Accredited by NAAC with A Grade

SUDHINDRA NAGARA, BENJANAPADAVU, BANTWAL, MANGALURU - 574219

AMMEMBAL SUBBA RAO PAI FOUNDER

AIC NITTE INCUBATION CENTRE

K-tech

CERTIFICATE

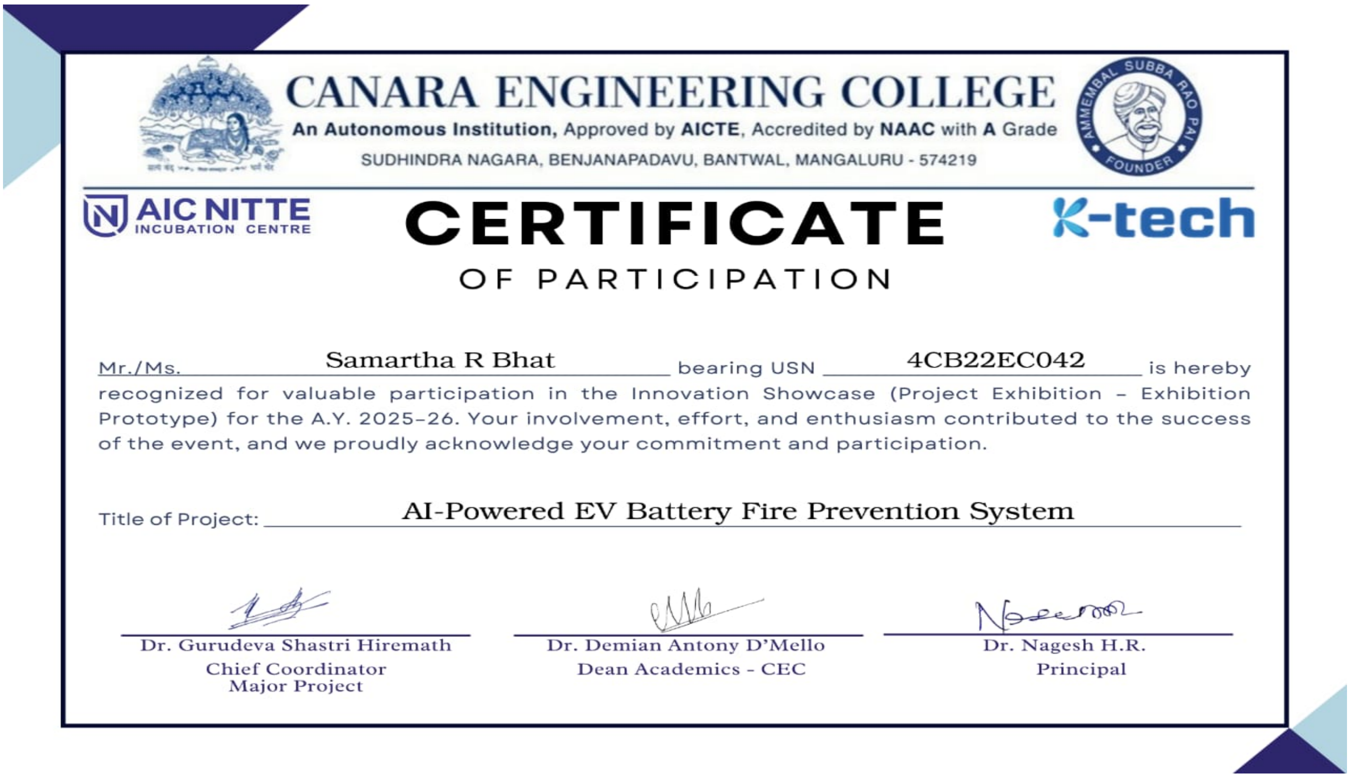
OF PARTICIPATION

Mr./Ms. Rashmi Rao B bearing USN 4CB22EC035 is hereby recognized for valuable participation in the Innovation Showcase (Project Exhibition – Exhibition Prototype) for the A.Y. 2025-26. Your involvement, effort, and enthusiasm contributed to the success of the event, and we proudly acknowledge your commitment and participation.

Title of Project: AI-Powered EV Battery Fire Prevention System

Dr. Gurudeva Shastri Hiremath Chief Coordinator Major Project	Dr. Demian Antony D'Mello Dean Academics - CEC	Dr. Nagesh H.R. Principal

Figure B.1: Certificate of Member 1



CANARA ENGINEERING COLLEGE

An Autonomous Institution, Approved by AICTE, Accredited by NAAC with A Grade

SUDHINDRA NAGARA, BENJANAPADAVU, BANTWAL, MANGALURU - 574219

AIC NITTE INCUBATION CENTRE

K-tech

CERTIFICATE

OF PARTICIPATION

Mr./Ms. Samartha R Bhat bearing USN 4CB22EC042 is hereby recognized for valuable participation in the Innovation Showcase (Project Exhibition – Exhibition Prototype) for the A.Y. 2025-26. Your involvement, effort, and enthusiasm contributed to the success of the event, and we proudly acknowledge your commitment and participation.

Title of Project: AI-Powered EV Battery Fire Prevention System

Dr. Gurudeva Shastri Hiremath
Chief Coordinator
Major Project

Dr. Demian Antony D'Mello
Dean Academics - CEC

Dr. Nagesh H.R.
Principal

Figure B.2: Certificate of Member 1