International Journal of Innovative Research in Engineering
*Volume 7, Issue 3 (May - June 2026), PP: 207-216*
https://www.doi.org/10.59256/ijire.20260703020
*www.theijire.com*
***ISSN No: 2582-8746***

# Battery Performance Monitoring and Control Using Machine Learning

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**How to cite this paper:**
Gaana H[1], Harsha K[2], Nandan Kumar M S [3], Vishwas N Gowda[4], Punyashekar[5], "Battery Performance Monitoring and Control Using Machine Learning", IJIRE-V7I3-207-216.



**Abstract:** *This paper presents the design and implementation of a real-time battery performance monitoring and control system using an ESP32-based embedded platform and data-driven decision logic. The proposed system continuously acquires battery voltage, current, and temperature using INA219 and LM35 sensors and processes these parameters to evaluate battery condition, operational safety, and performance status. Unlike conventional battery-monitoring methods that only display raw sensor readings, the developed system interprets sensed data through structured threshold-based decision rules derived from dataset analysis, enabling automatic classification of battery states such as normal operation, overcharge, deep discharge, overheat, thermal critical condition, high load stress, and short-circuit risk. In addition to state classification, the system estimates key battery indicators, including State of Charge (SoC) and State of Health (SoH), to provide a more informative assessment of battery condition. The processed results are displayed locally through a 16×2 LCD and remotely through a web-based dashboard, ensuring real-time visualization and user accessibility. A control mechanism is also incorporated to activate a cooling device when temperature exceeds safe operating limits, thereby improving battery protection and reducing the need for manual intervention. The overall design follows a modular architecture consisting of sensing, processing, decision, output, and control stages, making the system compact, low-cost, and scalable. By integrating sensor-based monitoring with embedded intelligence, the proposed approach enhances battery safety, operational efficiency, and reliability in practical applications such as electric vehicles, renewable-energy storage systems, portable electronics, and industrial battery management.*

**Key Words:** *Battery performance monitoring, battery management system, ESP32, data-driven decision logic, state of charge, state of health, real-time monitoring, temperature-based cooling control, web-based dashboard, embedded battery safety system.*

## I.INTRODUCTION

Battery monitoring systems have become a fundamental part of modern energy-storage applications because battery safety, efficiency, and lifetime depend strongly on continuous supervision of internal and external operating conditions. Recent work on intelligent battery management for electric vehicles has emphasized the growing need for structured datasets, algorithm-aware monitoring, and smarter estimation frameworks that move beyond simple measurement-only systems [1]. Parallel review studies on battery fault detection have shown that failures often originate from electrical, thermal, and sensing abnormalities that require timely identification before they evolve into hazardous conditions [2]. In addition, recent advances in battery state estimation have highlighted that reliable battery operation depends on accurate tracking of operating states within the battery management system [3]. Comprehensive BMS reviews also confirm that monitoring, charging strategy selection, and thermal protection are now central to safe battery operation in electric mobility and energy-storage systems [4]. Among the various measurable parameters in a battery monitoring system, voltage, current, and temperature are the most critical because they directly reflect charge condition, load stress, and thermal safety. Recent IoT-based BMS research has demonstrated that real-time monitoring combined with communication capability can significantly improve accessibility and remote supervision of battery behavior [5]. Similar IoT-enhanced monitoring frameworks have shown that integrating SoC and SoH tracking into embedded platforms can provide more meaningful battery assessment than displaying raw values alone [6]. At the same time, recent data-driven fault diagnosis studies have shown that battery faults in EV-oriented BMS designs increasingly require intelligent interpretation of monitored data rather than fixed alarm-only systems [7]. Fault-diagnosis reviews for lithium-ion batteries further reinforce that abnormal battery behavior must be understood through coordinated analysis of multiple parameters instead of isolated threshold checks [8]. Conventional battery monitoring systems often suffer from important limitations because they usually measure only basic variables and leave interpretation to the user or to simple protection logic. Recent comprehensive reviews on EV battery fault detection have shown that traditional monitoring methods often lack sufficient diagnostic depth for early abnormality recognition [9]. Likewise, recent reviews on state-of-health estimation in hybrid electric vehicle batteries have emphasized that battery degradation cannot be understood from a single measured value, but requires systematic interpretation of operating conditions and historical behavior [10]. Broader reviews on SOH estimation methods have also pointed out that health indicators, degradation trends, and estimation strategies must be combined for meaningful battery assessment [11]. In the same direction, systematic mapping studies on battery state estimation techniques show that modern BMS research is moving toward more integrated frameworks that combine measurement, estimation, and intelligent analysis [12]. The need for intelligent decision-making becomes even more important when battery systems must respond automatically to abnormal voltage, current, or temperature conditions in real time. Recent work on sensor fault diagnosis using multi-method fusion demonstrates that sensor reliability and condition interpretation are essential for dependable battery monitoring [13]. Advanced learning-based state-of-charge estimation studies have further shown that SOC accuracy can be affected by wide operating conditions, especially temperature variation, which makes intelligent processing increasingly important [14]. Research on aging abnormality detection also shows that battery behavior changes with degradation and may not be captured properly by static observation alone [15]. Similarly, recent data-driven SOH estimation studies confirm that modern battery monitoring is shifting toward embedded intelligence and decision-assisted analysis instead of passive measurement [16]. Motivated by these developments, the present work focuses on a practical embedded battery monitoring system that combines real-time sensing with data-driven decision logic for safer and more informative battery supervision. Recent multimodal SOH research based on open EV data highlights the value of combining multiple information sources for robust battery evaluation [17]. Domain-knowledge-guided machine-learning approaches further show that physically meaningful indicators can strengthen battery-state interpretation [18]. Studies on online SOC determination also indicate that charge estimation is closely influenced by battery health and should not be treated in isolation [19]. In the same context, recent reviews of SOH estimation and battery management confirm the importance of integrating monitoring, health estimation, and intelligent analysis in practical BMS design [20]. In line with this research direction, this paper presents an ESP32-based system that monitors voltage, current, and temperature in real time, estimates SoC and SoH, classifies conditions such as overcharge, deep discharge, overheat, thermal critical state, and load stress using structured decision logic, and activates a cooling mechanism while displaying results on both an LCD and a web dashboard [20].

## II.RELATED WORK / LITERATURE REVIEW

Z. Lyu et al. [1] presented a review toward intelligent battery management systems for electric-vehicle applications, emphasizing the importance of datasets, algorithmic frameworks, and future trends in battery intelligence. Their work is relevant to the present study because it highlights the transition from conventional monitoring to data-assisted battery supervision and intelligent state assessment.

Y. Shang et al. [2] reviewed recent progress in battery-system fault detection and discussed the growing importance of timely identification of abnormal battery conditions. This study supports the need for continuous monitoring and early warning functions in practical battery monitoring systems.

M. Jiang et al. [3] reviewed advances in battery-state estimation for battery management systems in electric vehicles. Their work underlines the importance of accurately estimating battery-related states in order to improve operational reliability, safety, and performance.

A. O. Ali et al. [4] provided a comprehensive review of battery management systems for electric vehicles, covering thermal management, charging strategies, and emerging technologies. Their findings show that modern BMS designs increasingly require integrated monitoring, protection, and control functions.

G. Krishna et al. [5] proposed an IoT-based real-time battery management system with long-range communication and FLoRa. This work is closely related to the present project because it demonstrates how battery parameters can be monitored continuously and communicated through connected platforms for remote supervision.

A. Gozuoglu [6] developed an IoT-enhanced battery management system for real-time SoC and SoH monitoring using an STM32-based programmable electronic load. This study is particularly relevant because it combines embedded monitoring with battery-health indicators, which closely aligns with the SoC and SoH estimation goals of the present work.

M. G. M. Abdolrasol et al. [7] reviewed advanced data-driven fault-diagnosis methods for lithium-ion battery management systems in electric vehicles. Their study confirms that intelligent diagnostic techniques are becoming increasingly important for battery safety and reliability in modern BMS implementations.

N. Gnanasekar et al. [8] discussed battery fault-diagnosis methods for EV lithium-ion batteries and correlated diagnostic

codes with battery management functions. Their work highlights the need for structured fault interpretation mechanisms in battery monitoring systems.
H. Li et al. [9] presented a comprehensive review on fault detection of lithium-ion batteries in electric vehicles. This paper reinforces the importance of continuous monitoring and abnormality detection for preventing unsafe operating conditions in practical battery systems.

J. Zhang and K. Li [10] reviewed state-of-health estimation methods for lithium-ion batteries in hybrid electric vehicles. Their study shows that SoH estimation is essential for evaluating battery aging, reliability, and long-term usability.

K. Tang et al. [11] reviewed health indicators, estimation methods, development trends, and challenges in lithium-ion battery SoH estimation. Their work provides strong support for including battery-health interpretation as part of a smart monitoring framework.

C. Tripp-Barba et al. [12] carried out a systematic mapping study on state-estimation techniques for lithium-ion batteries in electric vehicles. Their study shows the diversity of state-estimation approaches and confirms the importance of selecting suitable methods for embedded battery applications.

Y. Yan et al. [13] proposed a fault-diagnosis approach for lithium-ion battery sensors based on multi-method fusion. This paper is closely related to the sensing layer of the present project because accurate voltage, current, and temperature acquisition is fundamental to reliable battery-state classification.

D. Liu et al. [14] proposed an optimized multi-segment long short-term memory network strategy for state-of-charge estimation of power lithium-ion batteries over wide temperature conditions. Their study demonstrates that SOC estimation remains a major research topic, especially under varying thermal environments.

J. Du et al. [15] investigated aging abnormality detection in lithium-ion batteries using feature engineering and deep learning. Their work is relevant because it shows that battery monitoring systems increasingly aim not only to measure parameters but also to identify degradation-related abnormalities.

S. Rout et al. [16] presented a data-driven method for estimating the state of health of lithium-ion batteries. This study further confirms the usefulness of data-based battery analysis for improving health assessment beyond conventional fixed-threshold monitoring.

H. Liu et al. [17] developed a multi-modal framework for battery state-of-health evaluation using open-source electric-vehicle data. Their work shows that combining multiple information sources can improve the robustness of battery-health evaluation.

A. Lanubile et al. [18] proposed a domain-knowledge-guided machine-learning framework for lithium-ion battery state-of-health estimation. Their study demonstrates that combining battery-domain knowledge with data-driven analysis can enhance the interpretability and effectiveness of monitoring systems.

C. Armenta-Deu [19] studied online state-of-charge determination in lithium-ion batteries while considering the influence of state of health. This work is significant because it shows that SoC and SoH are interrelated and should be interpreted together in practical battery supervision systems.

M. Li et al. [20] reviewed state-of-health estimation and battery management with emphasis on health indicators, models, and machine-learning methods. Their work highlights the growing movement toward intelligent battery monitoring frameworks that integrate sensing, estimation, and decision-support functions.

From the above studies, it is clear that recent research has strongly focused on advanced battery management systems, EV-oriented fault detection, SoC and SoH estimation, IoT-enabled monitoring, and data-driven intelligent analysis. However, most reported works emphasize advanced estimation models, review-oriented studies, or large-scale EV battery applications, while a compact embedded system that combines real-time voltage, current, and temperature monitoring with lightweight decision-based battery-state classification and local control remains practically valuable. Therefore, a simple ESP32-based battery monitoring and control system with SoC, SoH, web visualization, and automatic safety response offers an effective and low-cost contribution for real-time battery supervision.

## III.SYSTEM OVERVIEW AND PROBLEM FORMULATION

Battery-powered systems are widely used in electric vehicles, renewable-energy storage units, portable electronics, and embedded devices, where safe and reliable operation depends on continuous observation of key battery parameters. In practical operation, abnormal conditions such as overcharge, overheating, deep discharge, and excessive current stress can significantly degrade battery performance and may also create serious safety risks. According to the project report, overcharging can damage battery cells, overheating can reduce battery lifespan, deep discharge can cause performance degradation, and high current can create stress that may lead to battery failure. These issues become more critical in systems where monitoring is manual or limited to displaying raw sensor readings without intelligent interpretation.

Conventional battery-monitoring approaches generally measure only basic quantities such as voltage and temperature and present them to the user for manual observation. Although some existing systems include simple protection features, they often lack automatic decision-making, predictive capability, and multi-parameter interpretation. As highlighted in the report, such systems do not classify battery condition, require continuous human supervision, and provide limited safety support when abnormal conditions occur. Therefore, a major problem in present battery-powered applications is not only the absence of sensing, but the absence of embedded intelligence capable of converting sensed data into actionable information and timely control decisions.

To address this problem, the proposed system introduces a Battery Performance Monitoring and Control System based on real-time sensing and structured decision logic. The system continuously reads voltage, current, and temperature using appropriate sensors and processes these measurements using a data-driven threshold-based decision model implemented on the ESP32 platform. Instead of only showing measured values, the system interprets them to classify the battery condition into meaningful operating states such as normal operation, overcharge, deep discharge, overheat, thermal critical condition, high load stress, and short-circuit risk. In addition, the system estimates State of Charge (SoC) and State of Health (SoH), thereby providing the user with a more informative assessment of battery status.

The overall objective of the proposed system is to develop a compact, low-cost, and intelligent embedded platform for real-time battery monitoring, classification, and control. As stated in the report, the main objectives are to monitor battery parameters, classify battery condition using data-driven decision logic, calculate SoC and SoH, provide real-time visualization through an LCD and web interface, and implement automatic control actions such as cooling activation. By combining sensing, processing, visualization, and protection in a single ESP32-based framework, the proposed system aims to improve battery safety, reduce human intervention, and enhance operational efficiency in practical battery-management applications.

## IV.SYSTEM ARCHITECTURE AND WORKING PRINCIPLE

### A. Overall Architecture

The proposed battery performance monitoring and control system follows a simple embedded architecture composed of three main layers: the sensing layer, processing layer, and output/control layer. In the sensing layer, the system acquires battery-related parameters such as voltage, current, and temperature using the INA219 and LM35 sensors. In the processing layer, the ESP32 microcontroller reads the acquired sensor data, performs conversion and filtering, calculates State of Charge (SoC) and State of Health (SoH), and applies threshold-based decision logic to determine the battery condition. In the output/control layer, the processed information is displayed to the user through a 16×2 LCD and a web dashboard, while a cooling mechanism is activated when temperature exceeds the safe operating limit. This modular structure improves clarity, simplifies implementation, and supports real-time battery supervision and protection.

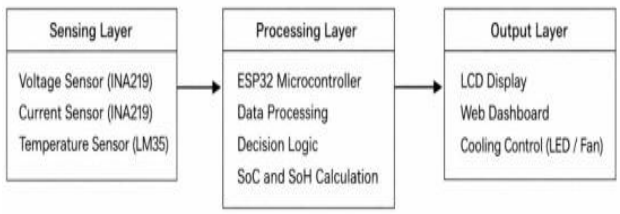


*Figure 1. Layered system architecture of the proposed battery performance monitoring and control system.*

The overall operational flow begins with sensor data acquisition, followed by embedded processing in the ESP32, battery-state classification using decision logic, and output generation through display and control actions. The report also describes the architecture as modular, reliable, and efficient, with the system designed for automatic operation without requiring continuous user intervention.

### B. Hardware Components

The proposed system is implemented using low-cost and widely available embedded hardware components. The ESP32 development board acts as the central controller and handles sensing, processing, Wi-Fi communication, decision-making, and output control. The INA219 sensor is used for battery voltage and current monitoring, while the LM35 temperature sensor measures battery temperature in real time. A 16×2 LCD with I2C interface is used for local display of battery parameters and classification results. A TP4056 charging module is used along with the Li-ion battery and power source components to support charging and system powering. A 5 V relay module is employed to switch the cooling fan, which is activated during high-temperature operation. Additional supporting elements such as breadboard connections, wiring, and a load interface are also part of the implementation.

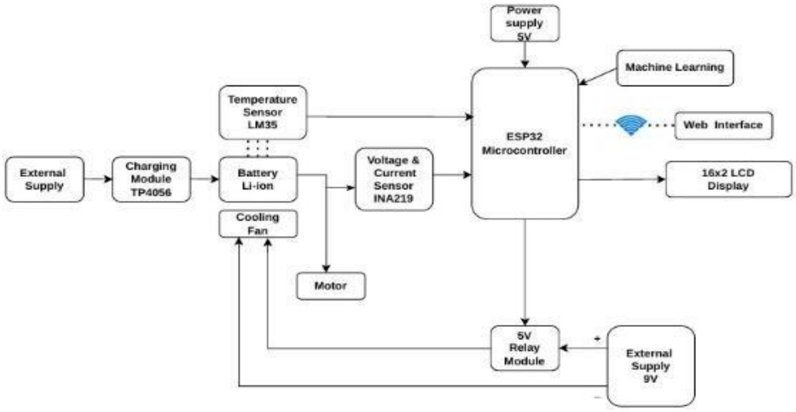


*Figure 2. Hardware block diagram of the proposed ESP32-based battery monitoring and control system.*

As shown in Figure 2, the Li-ion battery with TP4056 charging arrangement supplies the system, the INA219 module measures current and voltage, the LM35 provides temperature input to the ESP32, and the processed outputs are delivered to the LCD and relay-driven cooling fan. This hardware arrangement supports measurement, interpretation, display, and protection within a single embedded platform.

### C. Working Principle

The working principle of the proposed system is based on continuous sensing, embedded processing, condition classification, and automatic control. First, when the system is powered on, the sensors begin collecting voltage, current, and temperature data. The ESP32 then reads these values and performs necessary conversion and filtering. After preprocessing, decision logic is applied to classify the battery condition according to predefined thresholds. Based on this classification, the system updates the LCD and web dashboard with live battery information and activates the cooling mechanism if an abnormal temperature condition is detected. The report describes this operating sequence as: system power-up, sensor acquisition, ESP32 data reading, processing, decision logic application, classification, result display, and cooling activation when required.

To represent user interaction, the report includes a use-case view in which the user can monitor battery parameters, view battery status, receive alerts, and observe system output, while the system performs data acquisition and processing automatically. This supports the practical objective of minimizing human effort while maintaining continuous safety monitoring.

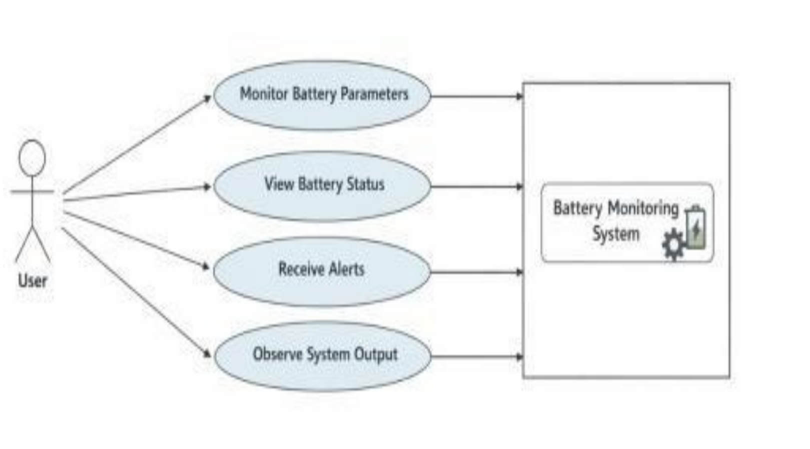


*Figure 3. Use-case diagram of the battery monitoring system showing user interaction with monitoring, status viewing, alert reception, and output observation.*

The internal data flow of the system is also structured into two levels. At Level 0, the flow is represented as Sensor Data → ESP32 → Output (Display + Control). At Level 1, the detailed flow consists of Sensor Input, Data Processing, Decision Logic, and Output Generation. In this sequence, voltage, current, and temperature are collected first, then converted and filtered, classified using threshold-based rules, and finally used to generate display updates and control actions. This clearly explains how the system transforms raw sensor readings into intelligent battery-status outputs.

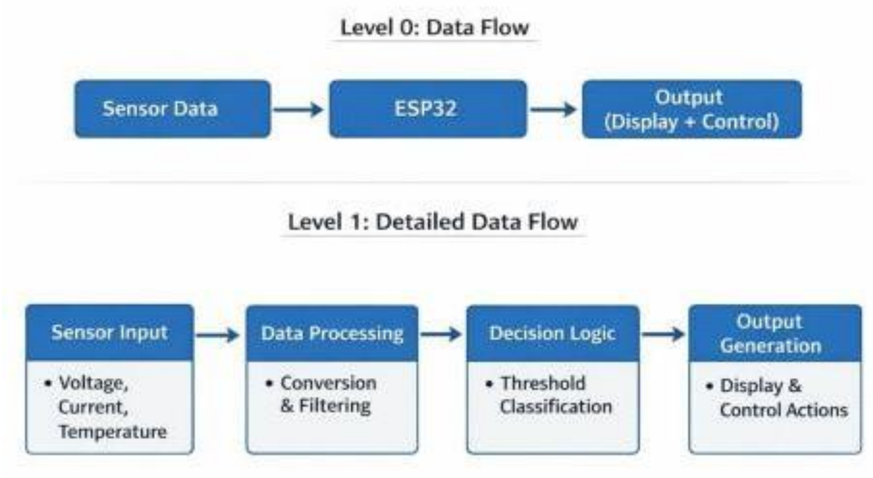


*Figure 4. Level-0 and Level-1 data flow diagrams of the proposed battery monitoring and control system.*

## V.MATHEMATICAL MODELING AND DECISION LOGIC

### A. State of Charge (SoC) Calculation

The State of Charge (SoC) is used to estimate the remaining battery charge level as a percentage. According to the report, the SoC is calculated from the measured battery voltage using a linear mapping between the lower cut-off voltage and the fully charged voltage. The implemented formula is

$$SoC = \left(\frac{V - 3.0}{4.2 - 3.0}\right) \times 100 \qquad (1)$$

where $V$is the measured battery voltage in volts. In this formulation, **3.0 V** corresponds to a fully discharged condition and **4.2 V** corresponds to a fully charged condition. The output SoC range is therefore from **0% to 100%**. This equation enables the system to estimate battery charge level in real time and present it to the user through the LCD and web dashboard.

### B. State of Health (SoH) Estimation

The State of Health (SoH) is used to estimate the overall condition of the battery by considering the effect of operating stress factors. In the report, the SoH is represented using a rule-based formulation that starts from an ideal health value and subtracts degradation contributions related to temperature, current stress, and voltage degradation. The implemented concept is expressed as

This equation reflects the idea that battery health decreases when the battery is subjected to elevated temperature, excessive current, or harmful voltage conditions. Unlike SoC, which indicates immediate charge level, SoH provides a broader indication of battery condition and long-term usability. In the proposed system, SoH is not derived from complex electrochemical modeling; instead, it is estimated through embedded rule-based logic to provide a practical and lightweight health indicator.

### C. Battery State Classification Logic

The core intelligence of the system lies in its threshold-based battery-state classification algorithm derived from dataset analysis. The embedded logic continuously evaluates the measured voltage, temperature, and current values and assigns the battery to a specific operating condition. According to the report, the implemented classification rules are as follows:

If $V < 3.0 \rightarrow$ Deep Discharge (3)
If $V > 4.25 \rightarrow$ Overcharge (4)
If the voltage remains within the normal band, then temperature is checked:
If $T > 50 \rightarrow$ Thermal Critical (5)
Else if $T > 40 \rightarrow$ Overheat (6)
If neither abnormal voltage nor abnormal temperature is observed, then the current condition is evaluated:
If $I > 1200 \rightarrow$ Short Circuit Risk (7)
Else if $I > 800 \rightarrow$ High Load Stress (8)

Else → Normal Operation (9)

This structured decision model allows the system to move beyond raw sensing and provide automatic battery-condition interpretation. Through this approach, the ESP32 can identify unsafe operating states in real time and trigger appropriate output and control actions, such as display alerts and cooling activation.

## VI.HARDWARE AND SOFTWARE IMPLEMENTATION

### A. Hardware Implementation

The proposed system is implemented using an ESP32-based embedded platform that integrates sensing, processing, display, and control functions into a single low-cost monitoring unit. As illustrated in **Figure 2**, the core hardware components include an ESP32 development board, an INA219 sensor module for voltage and current measurement, an LM35 temperature sensor, a 16×2 LCD with I2C interface, a TP4056 charging module, a Li-ion battery and power supply arrangement, a 5 V single-channel relay module, and a cooling fan or LED-based control output. The report also lists breadboard and wiring connections as required support hardware for interfacing the modules.

In the hardware arrangement, the INA219 is used to sense battery voltage and current, while the LM35 provides real-time temperature information to the controller. The ESP32 acts as the central processing unit and reads these sensor values continuously. The output section consists of two parts: a local display unit through the 16×2 LCD and a control path through the relay module. When abnormal temperature conditions are detected, the relay drives the connected cooling device, such as a fan, to enhance thermal safety. According to the block diagram and working description in the report, the battery supplies power to the system, the ESP32 receives sensor data, the processed results are displayed on the LCD and web dashboard, and the cooling system is activated when the temperature becomes high.

### B. Software Environment

The software implementation of the proposed system is carried out in the Arduino IDE using C/C++ under the Arduino framework. The report specifies that the main software platform is the ESP32 embedded system, and the monitoring dashboard is accessed through a web browser using Wi-Fi-based local server communication. The selected software tools were chosen for their simplicity, availability, and compatibility with embedded development.

The implementation uses several standard libraries to support sensing, communication, and display operations. The WiFi.h library is used for wireless connectivity, WebServer.h is used to create the web-based monitoring dashboard, Wire.h supports I2C communication, Adafruit_INA219 is used for voltage and current sensing, and LiquidCrystal_I2C is used to control the LCD display. Together, these tools provide the required software support for real-time data acquisition, user visualization, and embedded decision-based control.

### C. Embedded Algorithm Flow

The embedded algorithm follows a modular sequence of data acquisition, filtering, processing, classification, display, and control, as described in the report. At the first stage, the system continuously acquires sensor data from the INA219 and LM35 modules. The data-processing module then converts the raw sensor values into meaningful electrical and thermal parameters and applies averaging-based filtering to reduce noise. This ensures that the subsequent classification stage operates on more stable input values.

After preprocessing, the ESP32 applies the embedded decision-logic algorithm derived from dataset analysis. This logic classifies the battery condition according to predefined thresholds for voltage, temperature, and current. The report states that the implemented decision model identifies states such as deep discharge, overcharge, thermal critical, overheat, short-circuit risk, high load stress, and normal operation. In parallel, the controller also computes State of Charge (SoC) and estimates State of Health (SoH), thereby extending the system beyond simple measurement into condition-aware battery interpretation.

As shown in Figure 5, the algorithm begins with system initialization, followed by real-time acquisition of battery voltage, current, and temperature. The ESP32 then processes the measured data, applies filtering where required, calculates SoC, and estimates SoH. Next, the embedded decision logic evaluates the measured conditions and classifies the battery state into deep discharge, overcharge, overheat, thermal critical condition, high load stress, short-circuit risk, or normal operation. Based on the classified result, the system generates suitable alert messages, updates the LCD and web dashboard, and activates the relay-driven cooling device whenever the temperature exceeds the predefined safety threshold. Finally, the cycle repeats continuously to ensure uninterrupted real-time battery monitoring, intelligent state classification, and protective control.

Once the battery state is classified, the output module updates the LCD display and the web-based dashboard with real-time battery parameters and system status. If the temperature exceeds the predefined safe threshold, the control module activates the cooling device. Thus, the complete embedded flow can be summarized as: sensor input → data processing → decision logic → output generation and control action. This modular algorithm enables continuous monitoring, automatic classification, and immediate protective response without requiring constant user intervention.

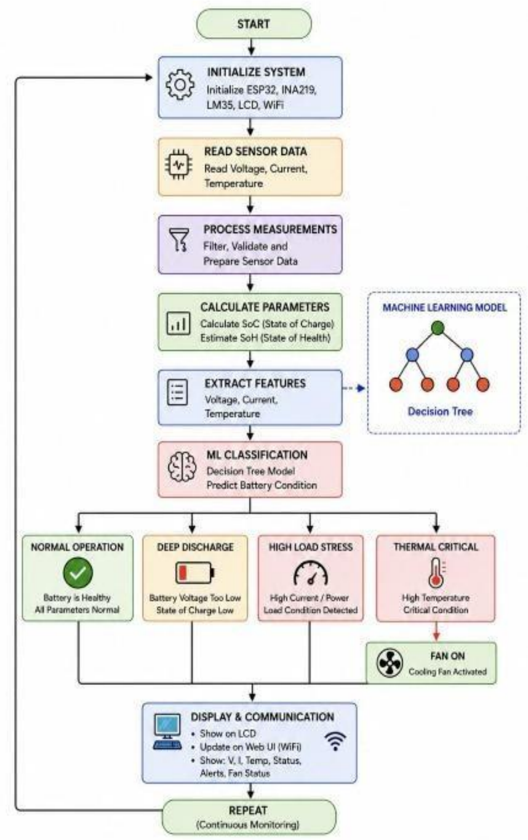


*Figure 5. Embedded algorithm flow of the proposed battery performance monitoring and control system.*

## VII.RESULT AND DISCUSSION

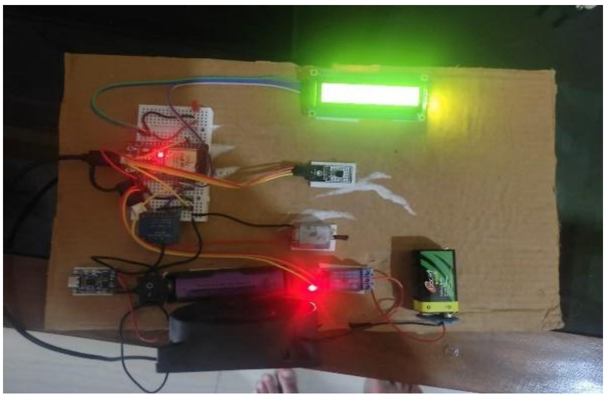

*Figure 6. Hardware prototype of the ESP32-based battery performance monitoring and control system with sensor modules, relay control unit, battery source, and 16×2 LCD display.*

The hardware prototype of the proposed Battery Performance Monitoring and Control System was successfully implemented using an ESP32 controller, battery source, INA219 voltage/current sensing module, temperature sensing unit, relay module, and 16×2 LCD display. As shown in the uploaded prototype image, the ESP32 is powered and operating correctly, while the LCD display is active, indicating successful communication between the controller and display section. The relay module is also powered, showing that the control section is ready to activate the cooling or protection mechanism when abnormal battery temperature or unsafe operating conditions are detected. The system continuously monitors battery voltage, current, and temperature, processes these values through the embedded decision logic, and classifies the battery condition into states such as normal operation, overcharge, deep discharge, overheat, thermal critical condition, high load stress, or short-circuit risk. The results confirm that the developed system can provide real-time battery status visualization and automatic safety response using a low-cost embedded platform. Therefore, the prototype demonstrates that the proposed ESP32-based monitoring system is suitable for practical battery safety applications, especially where simple, compact, and real-time supervision is required.


*Figure 7. AI Battery Sentinel dashboard showing real-time battery health, sensor readings, and intelligent battery-state classification under deep-discharge condition.*

The AI Battery Sentinel dashboard successfully displays the monitored battery parameters and decision output in a clear real-time format. From the dashboard, the measured battery voltage is 2.38 V, current is 795 mA, and temperature is 10.6°C. The calculated State of Charge (SoC) is 76%, while the State of Health (SoH) is 89.0%, indicating that the battery still has acceptable health but is presently operating under an unsafe voltage condition. Since the measured voltage is below the safe lower limit of 3.0 V, the system correctly classifies the battery status as Deep Discharge. The AI inference section further supports this decision by assigning the highest priority to the deep-discharge condition, while other risks such as overcharge, overheat, thermal critical condition, short-circuit risk, and high-load stress remain comparatively low. This result confirms that the proposed ESP32-based battery monitoring system can not only measure voltage, current, and temperature but also interpret the battery condition intelligently and provide meaningful warning information to the user. Therefore, the dashboard output validates the effectiveness of the proposed monitoring, classification, and visualization approach for real-time battery safety supervision.

## VIII.PRACTICAL APPLICATIONS

The proposed battery performance monitoring and control system can be applied effectively in electric vehicles(EVs), where continuous observation of battery voltage, current, and temperature is essential for safe and reliable operation. In EV systems, batteries are frequently exposed to varying load demands, charging and discharging cycles, and thermal stress. Under such conditions, the ability of the proposed system to identify abnormal states such as overcharge, deep discharge, overheat, high load stress, and short-circuit risk can improve battery safety and reduce the possibility of failure. In addition, the estimation of State of Charge (SoC) and State of Health (SoH) can support better battery-status awareness in EV battery management applications.

In renewable energy storage systems, such as solar-battery backup units and small DC energy-storage platforms, the proposed system can be used to supervise battery condition in real time and improve operational reliability. Since renewable-energy batteries often operate continuously over long charge-discharge cycles, monitoring parameters such as temperature, voltage, and current is important for preventing degradation and extending service life. The embedded decision logic and automatic cooling control included in the proposed design make it suitable for such energy-storage environments, where unattended operation and safety are critical.

The system is also highly suitable for portable electronics, where compactness, low cost, and efficient battery monitoring are important. Devices such as portable power packs, smart tools, and handheld systems can benefit from real-time battery-status indication, SoC estimation, and overheating alerts. Because the proposed design is based on the ESP32 platform and uses lightweight embedded logic without requiring cloud dependence, it can be adapted to portable battery-powered devices where power efficiency and simple implementation are important design factors.

## X.CONCLUSION

The proposed Battery Performance Monitoring and Control System demonstrates an effective embedded solution for real-time battery supervision by integrating voltage, current, and temperature sensing with structured decision-based condition analysis on an ESP32 platform. The system successfully combines continuous parameter monitoring, automatic battery-state classification, State of Charge (SoC) calculation, and State of Health (SoH) estimation to provide a more meaningful interpretation of battery behavior than conventional display-only monitoring methods. In addition, the integration of a 16×2 LCD and web-based dashboard enables clear real-time visualization, while the relay-driven cooling mechanism provides immediate protective action when unsafe thermal conditions are detected. Through this combination of sensing, classification, display, and control, the system improves battery safety, reduces the need for manual supervision, and enhances operational efficiency. Owing to its compact design, low cost, and practical functionality, the proposed system is well suited for battery monitoring applications in electric vehicles, renewable energy storage, portable electronics, and industrial battery systems.

## XI.FUTURE SCOPE

The proposed battery performance monitoring and control system can be extended in several important directions to improve its practical value and research depth. First, the present work should be validated through real hardware testing under different load conditions, charging profiles, and thermal environments in order to confirm the robustness of the sensing, classification, and control logic in real operating scenarios. Second, the system can be enhanced with cloud or IoT-based data logging so that battery data can be stored, analyzed, and accessed remotely over long periods. Third, future versions may incorporate predictive analytics to forecast battery degradation, failure trends, or abnormal operating patterns before critical conditions occur. In addition, the current threshold-based logic can be upgraded by integrating a true machine learning model for more adaptive and intelligent battery-state prediction, since the present report explicitly excludes real-time on-device ML training. The system may also be extended to support a multi-cell battery pack instead of a single-battery arrangement, enabling wider application in EV and energy-storage systems. A mobile application dashboard can further improve user accessibility by providing real-time monitoring and alerts through smartphones. Finally, the design can be strengthened with advanced protection circuitry, including industrial-grade overcurrent, overvoltage, thermal, and balancing protection mechanisms, to make the system more suitable for large-scale and safety-critical battery management applications.

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