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AI POWERED HYBRID MACHINE LEARNING AND RNN BASED PREDICTIVE BATTERY MANAGEMENT SYSTEM FOR ELECTRIC VEHICLES

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Abstract : With the growing shift toward electric mobility, the need has increasingly become critical for reliable and smart Battery Management Systems (BMS). This work details development of an AI driven hybrid Predictive Battery Management System for electric vehicles delivering advanced diagnostics plus safety controls using embedded technologies. The proposed system integrates a suite of sensors along with an embedded platform to continuously monitor battery voltage, current, temperature, state of charge, state of health, and physical condition. Data transmits to a dashboard using the cloud simultaneously plus processes on the device locally to respond promptly for remote visualization. Historical battery data is used in order to train machine learning models including Autoencoders, Random Forest classifiers, as well as Long Short-Term Memory (LSTM) networks. These models are fine tuned to identify abnormal behavior and predict the deterioration. This allows for predictive maintenance. Layered AI is considered as it is a fusion of time series analysis and classification methods, which can lead to enhanced fault prediction. Furthermore, incorporating certain edge computing capabilities means that the solution can take its own independent safety measures in urgent situations instead of relying on cloud infrastructure. This work presents prototype that work with the Raspberry Pi hardware and custom sensors. It proves the enhanced operational safety, minimize sudden accidents and prolong battery life.

***IndexTerms* - machine learning, edge intelligence, fault detection, predictive maintenance, electric vehicle safety, battery health management, and real-time diagnostics**

I. INTRODUCTION

As fuel prices go up and concerns about the environment grow, electric vehicles (EVs) are gaining popularity. This shift has resulted in increased research into other energy sources. Electric vehicles (EVs) are more environmentally friendly and use less energy. But there are still big problems, like a short driving range and worries about battery safety, especially when it comes to overcharging and deep discharging. Smart battery monitoring systems are necessary to solve these problems. Traditional battery management systems (BMS) usually send alerts to users at the dashboard level. However, more recent studies show that integrating cloud and IoT technology could improve remote monitoring and alerting systems.

This study aims to develop a smart battery management system that leverages embedded systems and artificial intelligence to overcome the limitations of traditional BMS. The proposed approach integrates real-time battery parameter tracking with machine learning algorithms to identify early signs of failure or degradation. AI models, including random forest and recurrent neural networks, have shown effectiveness in predicting battery aging, estimating state of health (SOH), and preventing fire hazards. When a critical issue is detected, instant notifications can be delivered to both the user and the manufacturer via IoT-enabled platforms, enabling proactive safety responses.

II. RELATED WORK

For building a strong base for this paper, an extensive review of recent national and international research on Battery Management Systems (BMS) for electric vehicles (EVs) was conducted. The aim was to analyze advancements in AI-based battery monitoring and identify existing research gaps.

Li et al. [1] has studied, developed an advanced Deep Learning and CAN2 based cloud-connected BMS. 0b real-time data transmission and precise SOC estimation by multilayer perceptron models. Haripriya [2] develop algorithm for battery aging prediction via deep learning, augment better driving range estimation and better battery lifetime. Kumar [3] studied BMS optimization based on digital twin with functional neural network method.

Ardeshiri et al. [4] reviewed ML applications in BMS for state estimation and RUL prediction, with the significance of the contribution of smart algorithms towards enhancing diagnostic accuracy. Zheng [5] stressed thermal monitoring to combat thermal runaway-related issues.

So, Khawaja et al. [6] tried out, like, six different machine learning models to figure out SOC and SOH—random forest kinda stole the show in terms of accuracy. Meanwhile, Konkimalla [7] jumped into the world of AI-driven predictive maintenance, messing around with Weibull regression to predict failures Then there's Hsu [8], who pointed out that EV charging really needs some proper PHM.

Wahab et al. [9] built an IoT-enabled BMS for real-time diagnostics and remote monitoring. This system helps with predictive maintenance. Doan [10] used deep reinforcement learning to manage retired EV batteries in energy storage systems.

Sultan et al. [11] merged active cell balancing with AI-driven RUL prediction, achieving high accuracy using k-NN and random forest models. Lipu [12] analysed 78 papers on AI in BMS, classifying applications under groups including SOC estimation, fault diagnostics, and energy optimization using deep learning methods.

Kosuru et al. [13] improved a deep learning-based error detection method using an IB-DRN model to detect sensor errors and cyber security threats. Muhendis [14] discovers nervous systems, hereditary algorithms, and encourages the study of AI-based BMS, recognising the advantages of performance inwards alongside the challenges.

Geetha Lakshmi et al. [15] developed an innovative AI-driven diagnostic system for electric vehicle batteries. This system leverages machine learning to accurately forecast battery issues and assess their state of health using real-time sensor data. This advancement not only enhances precision but also facilitates effective predictive maintenance.

III. METHODOLOGY

AI-Powered Fault Management, Preprocessing, and Real-Time Data Collection: Multiple sensors are integrated into the proposed Smart AI-Driven Battery Management System (BMS) to continuously monitor important battery parameters like voltage, current, temperature, fire risk, and structural integrity. As the edge processor, a Raspberry Pi handles anomaly detection, normalization, and noise filtering. Normal, Alert, and Critical are the three categories into which the system divides battery conditions.

IoT-Enabled Cloud Integration: MQTT/HTTP protocols are used to send pre-processed data to a cloud platform for long-term storage and real-time monitoring. By examining past patterns, this makes remote diagnostics possible and makes predictive maintenance easier as shown in Figure 1.

Hybrid AI Model Architecture: A hybrid AI framework integrates the following:

- Real-time anomaly detection using machine learning models (Autoencoders, Random Forest).
- Recurrent neural networks based on LSTM for forecasting faults and modelling patterns of battery degradation.
- K-fold cross-validation is used during model training to maximize generalization and performance.

On-Device Inference and Decision Making: To carry out edge inference, the trained models are installed on the Raspberry Pi. While critical failures require prompt safety responses, detected faults set off automated alerts via SMS, email, or app notifications. For service-side action, every event is recorded in the cloud.

Predictive and Proactive Battery Management: The system increases battery safety, extends service life, decreases downtime, and boosts the operational reliability of electric vehicles by combining real-time fault detection with long-term predictive analytics as shown in Figure 2.

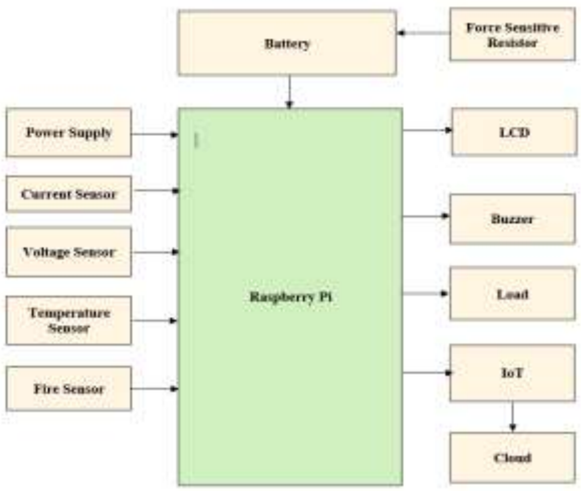

Figure 1. Hardware Block Diagram

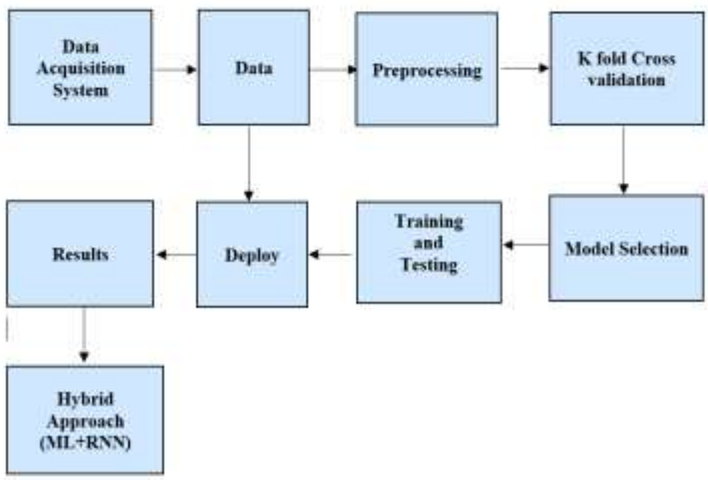

Figure 2. Software Block Diagram

IV. IMPLEMENTATION

The system is implemented into two main components are hardware and software. Each one of the components plays a crucial role in ensuring the overall functionality and performance of this project. The hardware part focuses on the physical components and their configuration, on the other side the software section details the logic, algorithms, and interfaces used to control and operate the system.

4.1 System Implementation

The final Schematic circuit diagram of the project was developed in PROTEUS Software circuit design and the diagram was finalized for PCB layout. The circuit diagram illustrated consist of the main controller is a Raspberry Pi, which acts as an edge computing unit and IoT gateway. The system uses an INA 219 current sensor and voltage sensing circuit to measure battery flow and voltage, which are fed into an ADS1115 ADC for high-resolution readings. It also uses a DS18B20 temperature sensor, fire sensor, and Force Sensitive Resistor to detect physical deformation or swelling. The system includes a buzzer for local feedback and an LCD display for real-time status data. All components are powered by 3.3V, 5V from the Raspberry Pi for low power consumption is as shown in Figure 3.

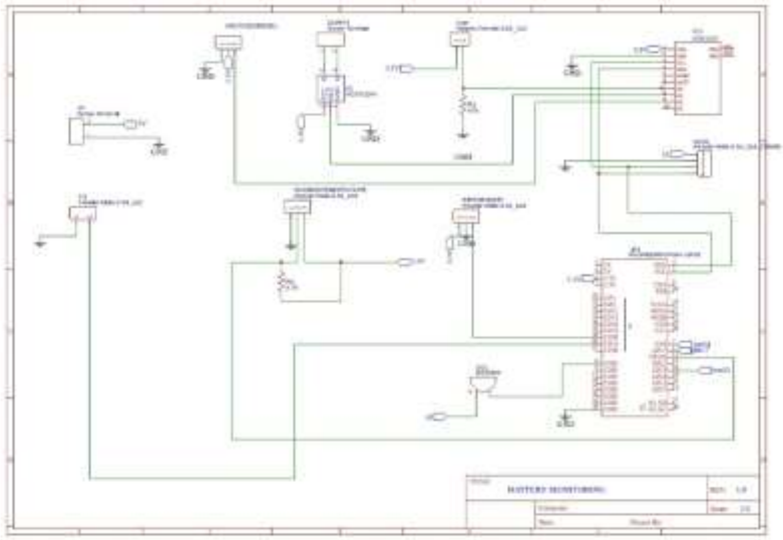

Figure 3. Schematic of the proposed system

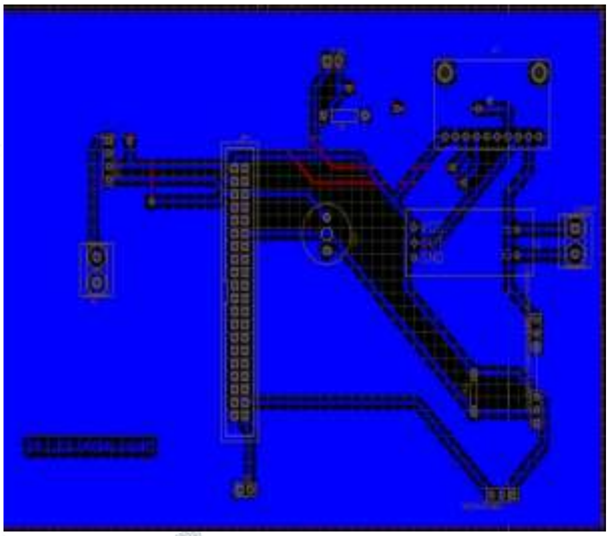

Figure 4. PCB Layout

The PCB layout of the Raspberry Pi GPIO header, ACS712 current sensor, ADS1115 ADC, voltage sensing terminals, fire sensor, force sensor, temperature sensor header, buzzer, and LCD connections is designed for easy connectivity and minimal interference. To minimize noise and signal loss, the PCB elements are laid out carefully, and the large ground plane helps ensure electrical stability by reducing electromagnetic interference. The arrangement efficiently manages power and signals, while the silkscreen labels make it easier to assemble and identify the components. You can see the layout in Figure 4.

4.2 Implemented Model

Its implementation has two halves. One is the mechanical system for applying the load and other is data acquisition system. Here the hardware set up works as the data acquisition system So the data are acquired manually from the data acquisition system by applying different load types and by inducing the different type anomalies to get the various types of data around 10, 000 data has been acquired manually to train the model for the better accuracy.
mechanical system consists of wheel and along with the display which consists of the how much speed the wheel is turning in terms of RPM and there is a switch provided by the mechanical system to turn on and off, and there is one more plug which can be used to connect to the battery box as shown in Figure 5.

Figure 5. Mechanical System

Figure 6. The battery Box

Here the battery is designed as per the load, So the lithium ion battery of capacity 2700 Mah with output power 3.7 Volt and the dimension is 18650, And the battery in terms connected to the main circuit where the Raspberry Pi model acts as a main controller with the other sensors being added to it. Here we are mainly using the to supply one for the Raspberry Pi and another will be to turn on the LCD screen because these two operate at different voltages as shown in Figure 6.

V. RESULTS AND DISCUSSIONS

This chapter presents a comprehensive analysis of the Smart Battery Monitoring System, covering dataset insights, anomaly detection, model performance, and test validations. The evaluation integrates exploratory data analysis (EDA), supervised learning results, and validation through induced fault scenarios. Figures generated from the dataset and test cases provide visual support to the discussion.

5.1 Dataset and Correlation Matrix

The dataset consists of 42,000 time-series samples with 12 features, including key sensor readings such as battery voltage, current, power, temperature, and FSR voltage (a proxy for mechanical bulging). The dataset spans ~23.3 hours at a 2-second median sampling interval. States are categorized as NORMAL (80%), ALERT (15%), and CRITICAL (5%). Anomalies such as battery_low, bulging_high_fsr, current_high, fire_detected, and temperature_high occur only in ALERT or CRITICAL states as shown in Figure 7.

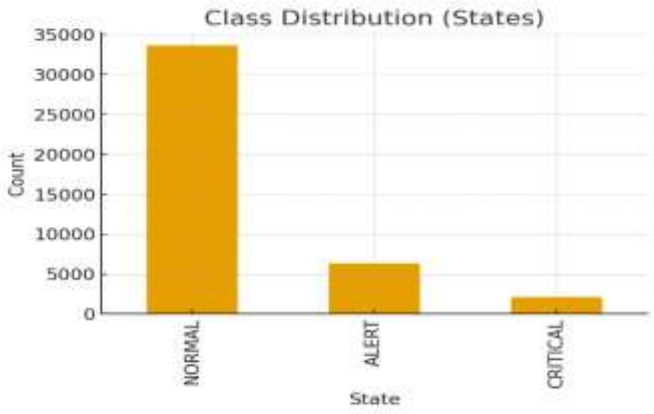

Figure 7. Class Distribution

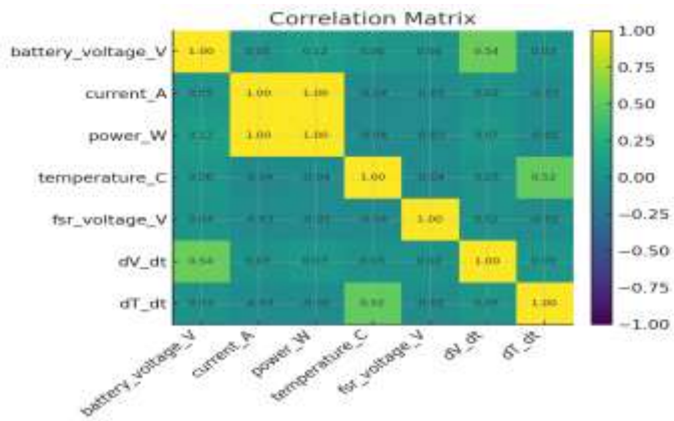

Figure 8. Correlation matrix of all parameter

Histograms from Figure 8, revealed bimodal distributions in battery_voltage_V and temperature_C, indicating distinct operating regimes. Correlation analysis showed a strong linear relationship between current_A and power_W (P=VI). Other features exhibited weak linear correlations, highlighting the suitability of non-linear models such as Random Forests. Boxplots confirmed intuitive associations: elevated temperature_C for temperature_high anomalies, and high fsr_voltage_V for bulging_high_fsr anomalies.

5.2 Model A: Battery State Classification and Model B: Anomaly Type Classification

A Random Forest Classifier was trained to categorize states into NORMAL, ALERT, and CRITICAL. The model achieved perfect accuracy (1.00) with flawless classification across all test samples. The most important features were temperature_C, battery_voltage_V, and power_W as shown in Figure 8.

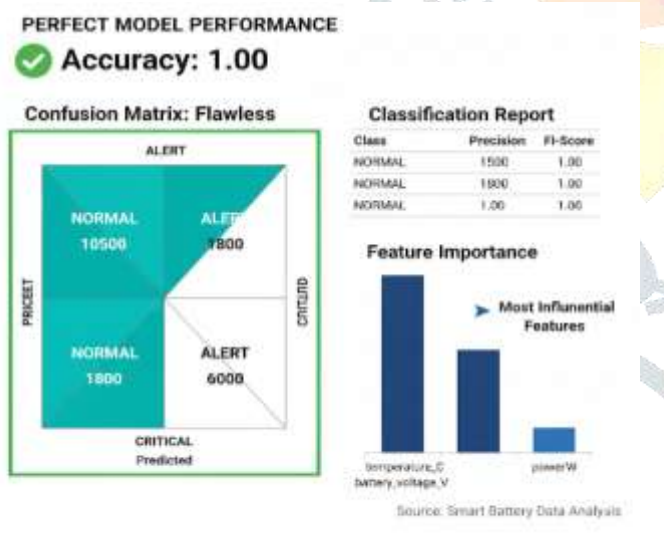

Figure 9: Battery State Classification

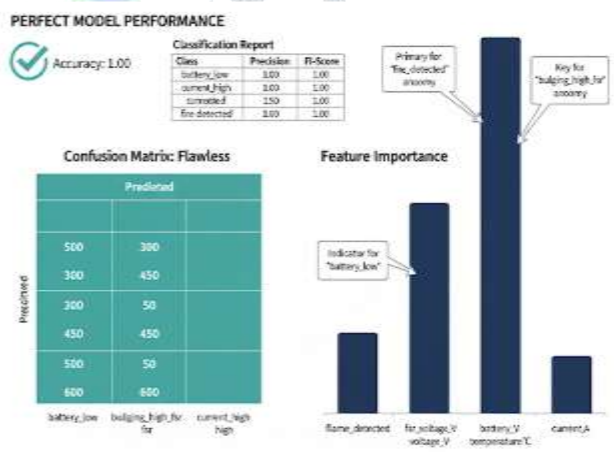

Figure 10. Anomaly Classification

The anomaly type classifier was trained on subsets where anomalies were present. It distinguished battery_low, bulging_high_fsr, current_high, fire_detected, and temperature_high with perfect performance (accuracy = 1.00). Feature importance analysis confirmed flame_detected, fsr_voltage_V, and battery_voltage_V as the primary indicators for their respective anomalies is as shown in Figure 9.

5.3 Model Validation under Severe Faults

A simulated severe fault scenario was tested (low voltage, high current, high temperature, and flame presence). The model correctly predicted CRITICAL state and fire detected anomaly with 100% confidence. This validates the model's deployment readiness as shown in Figure 10.

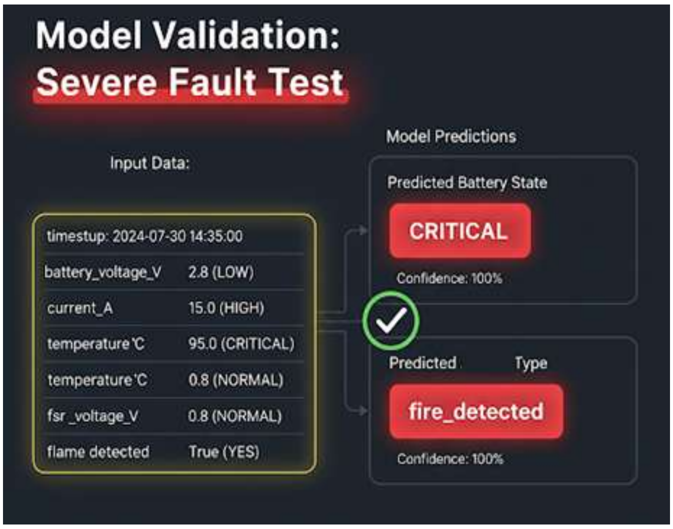

Figure 11. Model Validation

Table 1. Comparison of class with metrices

Class	Precision	Recall	F1-Score	Support
battery_low	1.00	1.00	1.00	406
bulging_high_fsr	1.00	1.00	1.00	396
current_high	1.00	1.00	1.00	398
fire_detected	1.00	1.00	1.00	90
temperature_high	1.00	1.00	1.00	390

In addition to continuous dataset evaluation, controlled test cases were executed to validate anomaly detection. Since real-time catastrophic faults are rare, anomalies were deliberately induced: disconnecting the battery (battery_low), pressing the battery to trigger FSR (bulging_high_fsr), applying overload (current_high), exposing to flame (fire_detected), and raising temperature (temperature_high). Classification Report (Table 1).

VI. Conclusion and Future Scope

The developed system for electric vehicle battery management combines embedded technology with real-time monitoring and predictive analysis using a hybrid model of machine learning and deep learning. It uses integrated wireless sensor networks, cloud connectivity, and intelligent decision-making capabilities. The system offers continuous monitoring of temperature, voltage, and current, predictive maintenance, and instant mobile notifications for users and manufacturers. The system detects abnormal conditions like overheating, fire, and battery bulging with high accuracy, and forecasts battery degradation trends. Cloud integration allows remote access to data and enhances long-term performance and safety risk analysis. This comprehensive integration improves battery safety, reliability, and lifespan, contributing to sustainable and intelligent mobility solutions.

The proposed smart battery monitoring system can be integrated into a System-on-Chip (SoC) design, reducing complexity and improving efficiency. The algorithm can be mapped to a VLSI-based implementation using System Verilog, enhancing real-time data acquisition, parameter monitoring, and decision-making functions for electric vehicles.

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