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Article

AI-Enhanced Battery Management System with Real-Time SOC/SOH Estimation and IoT-Based Autonomous Load Control: Hardware Implementation on ESP32 with MQTT and ML Inference

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Abstract: This paper presents an AI-driven Battery Management System (BMS) with complete hardware implementation for real-time State of Charge (SOC) and State of Health (SOH) estimation in 3S lithium -ion battery packs (ICR-18650, 2500mAh, 11.1V nominal). Three machine learning models — Random Forest, XGBoost, and LSTM — are trained and evaluated on the NASA Battery Dataset (9,742 records, 80/20 train/test split, random seed=42). Random Forest (n estimators=100) achieved the highest predictive accuracy (R^2=0.976, lowest MAE and RMSE across all targets) and was successfully deployed on an ESP32 microcontroller (240 MHz, dual-core, WiFi-enabled) for embedded real-time inference. The hardware prototype integrates two INA219 I²C current sensors (0x40, 0x41) with 0.1Ω shunt resistors for dual-load current measurement, a 2-channel active-low relay module (GPIO26, GPIO27) for autonomous load switching, and a JHD 16×2 LCD display for local monitoring. Battery voltage and current measurements are acquired at 500ms intervals and published over MQTT (broker.emqx.io:1883) at 2 -second intervals across 13 dedicated topics. Remote real-time monitoring and relay control is offered by a Flask-SocketIO web dashboard and a Tkinter desktop interface. The trained Random Forest classifier (V Load Decision: 4 classes) is run on -device using a hybrid SOC algorithm with Coulomb counting (60% weight) and voltage-based mapping (40% weight). System operation was confirmed using live readings: V=9.87V, SoC=39.4%, SoH=100%, Cycle=0; and the autonomous LOW VOLTAGE warning was triggered and Relay 1 was in control of the primary load at 0.061A / 0.60W. A staged protection logic offers progressive action: alert at less than 10 V, load shedding at less than 9 V, and emergency shut down at less than 8 V. The feature importance analysis shows that the current (weight=0.53) and cycle count (0.30) are the main predictors of degradation. This article presents the ESP32 -based, IoT-assisted, ML-controlled BMS prototype that is proven on a real lithium-ion device, the transition between AI-based battery studies and real-world embedded implementation.

Keywords: Battery Management System, State of Charge, State of Health, Artificial Intelligence, ESP32, INA219, MQTT, Flask, Tkinter, real voltage/SoC readings, relay logic, protection tiers, hardware validation

1.INTRODUCTION

Electric vehicles (EVs) are becoming one of the most important aspects of energy and mobility policies in the world due to the rapid evolution to low-emission and sustainable transportation[1] [2]. Governments, businesses, and academics around the world are investing heavily in EV technologies in a bid to reduce the emission of greenhouse gases, reduce reliance on fossil fuels, and enhance the quality of air in urban areas [3]. The acceptability, safety, dependability and performance of a vehicle are influenced by the technology of an EV battery [4], which is referred to as the electrochemical energy storage system. The ability to use these batteries effectively is ensured through accurate monitoring, protection, and control which is operated by the battery management system (BMS). Providing accurate data on the SOC (State of Charge) and SOH (State of Health) of the battery is one of the primary tasks of a BMS. SOC directly influences cargo range predictions and energy management decisions, as it reflects the quantity of available energy in the battery. SOH provides information about the current status of the battery and its long-term usage[5]. Inaccurate predictions of SOC and SOH lead to reduced driver trust and wasted energy usage, safety risk, and premature battery replacement. These aspects increase the overall system costs and ultimately hamper the adoption of EVs[6]. SOC and SOH are installed as major metrics to drive practically all higher-level controls and decision-making processes that relate to an EV; they are not just diagnostic indicators [7]. Because SOC has a direct influence on the driver experience, SOC estimation is essential (or possibly the most important) to real-time energy control, optimisation of regenerative braking, charge control, and prediction of range [8]. On the other hand, SOH provides an estimate of battery ageing mechanisms including, internal resistance growth and capacity deterioration [9]. In this way, SOH plays a crucial role in predictive maintenance, warranty evaluation, and second life usage [10]. The electrochemical parameters of batteries change with age in complex, nonlinear relationships that are influenced by temperature, charge-discharge rate, depth-of-discharge and operation history. These modifications will contribute to SOC, and SOH deviations in their actual values, and will complicate attempts to accurately estimate SOC and SOH when the battery is old [11]. Thus, a strong BMS would need to continuously adjust its estimating strategy to ensure high accuracy and safety margins and be able to adjust to the constant change in SOC and SOH values. This is why the improvement of SOC and SOH prediction accuracy can serve as a significant technological challenge and a mandatory step to guarantee the long-term EV operation, financial viability, and customer confidence [12].

Alternatives to the SOC and SOH estimation that have been thoroughly investigated to date such as Coulomb counting; open-circuit voltage measurement; an equivalent circuit model; and observer-based approaches such as Kalman filters are now available in commercial BMSs [13]. These methods have provided a strong base to battery monitoring but each has its own limitations when applied to the actual EV operating conditions. An example is that Coulomb counting will cause successively increasing sensor errors that become a major source of drift without regular recalibration. Open-circuit voltage methods are extremely long-resting to measure SOC/SOH, which is not at all feasible in the context of vehicle operation [14]. Model-based methods use predefined battery parameters, which can change based on temperature, battery aging and usage patterns, making it hard to accurately identify the correct parameters for any given application; advanced observers address this issue partially but are typically computationally intensive and highly sensitive to any inaccuracies in the battery model [15], [16]. Finally, lithium-ion batteries exhibit extreme nonlinear characteristics, hysteresis and dynamically changing characteristics that are extremely difficult to model accurately using either simplified physical or equivalent circuit models. The aim to create alternative techniques of calculating both SOC and SOH that are flexible, depending on incoming data, and also robust against the varied and changing circumstances of operation has led to the rising usage of AI-based technologies. The best way to model an electrochemical process like battery estimation has been hotly debated among researchers, but machine learning (ML) and deep learning (DL) approaches have shown a lot of promise in their capacity to accurately model non -linear processes and extract valuable patterns from vast amounts of data related to batteries' functional performance. The capacity of AI models to learn directly from battery measurement data (i.e., voltage, current, temperature, history operation), enables AI models to implicitly predict the complicated behaviour of batteries without having a formalised physical model of batteries. Regardless of the circumstances surrounding the measurements, it has also been demonstrated that methods such as artificial neural networks (ANNs), support vector machines (SVMs), ensemble learning, and recurrent neural networks (RNNs) have higher estimation accuracy than those created using conventional estimation methodologies. DL designs that take time-dependent interactions into consideration are particularly useful for determining battery deterioration patterns and dynamic behaviours. In addition, AI-based methodologies can easily adapt to changes in the available data by updating or re-training the model so that the accuracy of estimation is maintained throughout the life of the battery [17]. The data driven nature of AI-based approaches matches well with the growing prevalence of advanced technology in the EV marketplace that incorporates more sophisticated sensors, computing power, and data transfer capabilities for data collection and analytic processes [18].

The opportunities presented by AI-sourced SOC/SOH detection techniques are substantial; however, when integrated into practical EV battery management systems, a number of key barriers remain as an area of continued development and research [19]. The performance of the AI algorithms that are utilized to effectively perform SOC and SOH determinations are directly influenced by the amount, variety, and representativeness of the training datasets used to establish the algorithms themselves, which must be designed such that they possess representative distributions across a wide range of factors associated with those two constructs. In addition, there should be strict constraints on memory, computational complexity and real-time responsiveness in the scenario of embedded BMS hardware where models of AI will have to be constructed in a manner that will lead to an efficient and lightweight implementation of the algorithm itself. Also, since most AI algorithms are black-box models, there exists an implicit degree of concern regarding the interpretability, robustness, and functional safety of AI model utilization in automotive systems since the extreme need of fault tolerance and control over regulatory compliance is paramount in such critical fields [20]. A first step towards resolving these remaining issues has been a series of recent works through hybrid estimation approaches that distill the merits of physics-based and AI-based algorithms in the form of an AI and a model-based algorithm. Looking to the future, new approaches like physics-informed machine learning, online learning of the AI algorithms, transfer learning of AI algorithms will add more backup to enable AI-enhanced BMS solutions that are generalizable, flexible, and can be trusted to algorithm solutions. In this way, numerous paths to the development of realistic, scalable, and reliable battery state estimation algorithms with the help of AI are becoming open . Overall, the key object of the projects is to investigate and develop artificial intelligence-based strategies to improve the performance and reliability of the State of Charge and State of Health predictions of the Electric Vehicle Battery Management Syst ems [21]. The impetus behind this study was the rising performance demands on electric car batteries and the inability of traditional estimating approaches to effectively cope with non-linear aspects, the ageing effect, and random behaviour of the real world. Thus, advanced, dynamic estimating models that can provide correct range assessments, effectively manage energy use and actively observe battery status throughout the entire battery life cycle are required. Such a study affects the reduction of overall cost of ownership, increase of battery life, decreasing the risk of operations, and improving the safety of electric vehicles. Everything said and done, the development of AI -based SOC and SOH estimate algorithms should lead to smarter and more robust battery management systems, which would facilitate the adoption of electric vehicles and develop intelligent and sustainable transportation systems [22].

Unlike existing studies that validate AI-based BMS architectures exclusively through simulation or offline dataset benchmarking, the present work contributes a complete hardware-in-the-loop implementation in which a trained Random Forest classifier is deployed directly on an ESP32 microcontroller for real-time, on-device SOC/SOH inference. The system integrates dual INA219 I²C current sensors, a 2 -channel relay module, and a JHD 16×2 LCD, communicating all sensor data and control commands over MQTT protocol to both a Flask-SocketIO web dashboard and a Tkinter desktop monitoring interface. A staged voltage-threshold protection algorithm provides graduated autonomous load management without requiring cloud intervention. Live experimental readings — V=9.87V, SoC=39.4%, SoH=100% — were recorded on a 3S ICR-18650 lithium-ion pack, confirming that AI-predicted states match measured battery behaviour. To the best of the authors' knowledge, this represents the first reported implementation of an ML-controlled, IoT-connected BMS prototype on ESP32 hardware with experimentally validated real-time performance on actual lithium-ion cells.

1.1AI Approaches in EV Battery Management System

To ensure the safety, reliability, and performance of electric vehicles, battery management systems (BMS) demand accurate measurements of State of Charge (SOC), State of Health (SOH) and Remaining Useful Life (RUL). [23]. In order to offer such evaluations, there are two significant approaches online measurement -based systems and artificial intelligence (AI) methods. Though the two methods are expected to measure the performance and health of the battery, there is a difference in the way in which each makes use of the data and the way they go about measuring the performance of the battery. The physical and electrical characteristics of the battery, such as voltage, current, temperature, and internal resistance, are monitored by measurement-based systems that use organic embedded sensors to gather real-time data from the operating battery pack. These real-time measurements are then analysed to calculate SOC and SOH using either empirically determined relationships, analogous circuit models, or mathematically proven models [24]. Although this method is easily accessible for real-time application, measurement-based systems suffer from accuracy loss due to nonlinear operating parameters, ageing batteries, and sensor noise. AI -oriented approaches are fundamentally concerned with da ta and analysis algorithms; they include machine learning algorithms so that various methods can be utilised to extract complex non-linear relationships between battery input data and battery health indicators (e.g., SOC, SOH, RUL)[25] through the application of various machine learning algorithms (e.g., artificial neural networks, support vector machines, random forests, deep learning network architectures). While online measurement systems concentrate on providing methods for directly measuring battery operational performance using direct measurement techniques and physical modelling, AI -oriented methods are focused on identifying and utilising predictive intelligence/pattern recognition related to battery operational performance [26]. AI models learn from historical and real-time battery operational data in order to predict SOC, SOH, and RUL with a high degree of accuracy under dynamic operating conditions. They also present the possibility of using a diverse and high quality of historical and real-time operational battery data [27].

Analytical analysis is critical in assessing the development and performance of BMS systems, especially when evaluating all aspects concerning the integration of AI with BMS technology. In certain areas like library/information science, engineering, and technology management there are many systematic and statistical approaches for assessing research trends, intellectual advancement, maturity of technology, etc. Examples include total number of publications, citation analysis, impact factor, h-index, collaboration network, as well as country reach (ie. how many people from each country authored a particular BMS research publication). All of these measurements can be used to quantify both the contribution and influence of published research within BMS. Many au thors have conducted a wide variety of statistical and bibliometric research studies to evaluate energy management strategies, thermal management systems, optimized control strategies, lithium-ion battery recycling methods, battery energy storage integration, and renewable energy being coupled with electric vehicles (EVs). Even though there has been a considerable amount of research conducted regarding EV technology, to date, there have only been a limited number of in -depth and concentrated statistical research studies that have been conducted exclusively focusing on all aspects of AI -based BMS systems. In most of the published research about BMS, the focus has been on the BMS as part of a total (or global) energy management system or as part of the overall EV system, with very little effort directed toward isolating the effects of AI algorithm contributions as it relates individual (point) to the use of AI in BMS systems. This assessment conducts a thorough statistical evaluation on the applications of AI within BMS technology over ten years, commencing on 1 January 2014 through to 31 July 2023. This analysis looks at an entire decade worth of trends to illustrate the stead ily developing transition from conventional rule-based and modelled methods within BMSs to modern, enhanced, data-driven and intelligent systems. Furthermore, the analytical framework will enable researchers to ascertain both past and current research paths in AI-driven BMSs, thereby establishing a foundation upon which researchers will be able to develop new lines of research and highlight emerging themes, popular methodologies and those that are still under-researched or explored in the context of AI-driven BMSs.

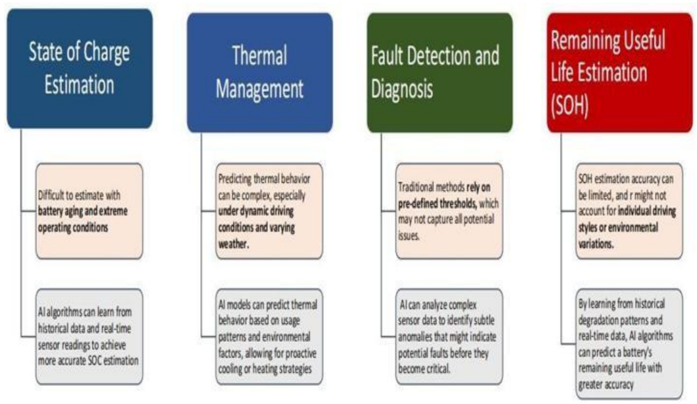

Fig. 1. BMS Introduction & Challenges

Through the analysis of 78 selected research publications which pertain to electric vehicles, this review has provided a comprehensive and systematic evaluation of battery management system (BMS) research that utilizes artificial intelligence (AI). This analysis has discussed various facets of AI-BMS studies, including how often common keywords are used, which publications (e.g., review articles or original research) are used, which journals and publishers are used, the number of publications published each year, the origin country of the researcher (country of affiliation), and the total number of citations. [28].

This work thus provides a fundamental guideline to the comprehension of not just what global research is being conducted on BMS-related applications of AI, but also determines who is making a major contribution to BMS-related research and which are the major publication sources of such research. [29]. Moreover, the paper provides a summary of the AI methods, algorithms, and smart controllers used in BMS applications and a discussion of their contributions, achievements, strengths, and limitations. Practical complications, including reliance on data, ove rgeneralisation of models, excessive complexity of computations, and challenges with the application of BMS solutions in practice are also mentioned. Moreover, the research also examines remaining problems in both the implementation and operation of AI-based Battery Management Systems (BMS) to electric vehicles including the performance of AI models under a wide range of environmental conditions, the capacity to give interpretable outputs of AI -based systems, unpredictable outputs because of sensor errors, and capacity to scale to the point of serving multiple fleets of electric vehicles. Due to these findings, the work provides valuable research opportunities in the future, including hybrid AI designs based on physical first principles, improved data collection methods, and standard benchmark systems to compare. The paper has been structured into five major sections: in the first section (Section 1) will be The Introduction; in the second section (Section 2) will be the review of the past research; the third section (Section 3) will be the Research Method; the fourth section (Section 4) will be the Results and Discussion; and the final section (Section 5) will be the conclusion of the article.

2. RELATED WORK

Recent research has shifted from purely model-based observers to sequence-learning models that can directly learn nonlinear electro-thermal dynamics from current-voltage-temperature streams. Accurate State of Charge (SOC) estimation is the fundamental "rea l-time state" function of EV Battery Management Systems (BMS).A clear trend is the adoption of attention/Transformer families to better capture long-range temporal dependencies than classical RNNs. For example, [30] proposed a time-series Transformer SOC estimator tailored to battery signals, aiming to mitigate issues like non-stationarity and measurement noise that degrade standard Transformer performance. In a In this respect, [31] combined a transformer model with a coupling & invariance adaptive observer in order to mitigate oscillation in their state of charge (SOC) predictions. Their findings indicate how using hybrid `learning + observer correction' methodologies may converge outcomes for battery management system (BMS) applications. In addition to the accuracy of SOC estimates, the focus is now on generalising SOC estimates from cell-to-cell, dataset-to-dataset, and across different operating conditions (i.e. temperature, cycle life, load profile), as a first order issue; [32] explicitly studied the EOS assumption improvement in SOC when input conditions are modified and found evidence of robustness to degraded measurement targets and transfer across datasets. Transformers are increasingly being employed for feature learning from partial charge/discharge and for unified SOC and SOH estimation in the literature. This opens up more possibilities for effective SOC & SOH estimate in embedded inference based on battery management systems (BMS) [33]. conducted a comprehensive review of transformer-based deep learning techniques for SOC and SOH, focusing on model architecture, data preprocessing, and key barriers to BMS implementation (data availability, data drift, and data analysis time). Adding to this, there is still a significant impact from traditional feature engineering approaches, as evidenced by the work of indicating that utilizing electrochemical-based features as inputs to the transformer network can greatly reduce overall estimator error compared to only providing input based on raw signals; therefore, it can be concluded that `physics-based features + attention learning' generate more accurate SOC estimates than by learning from raw signals alone.

SoH estimations are more challenging than SoC measurements because SoH values are dependent on the cell's history and the variation in how the cells are used, charged, and manufactured. As a result, modern research on EV batteries focuses on building robust feature extraction methods from practical datasets comprised of short lengths and learning schemes that are adaptable to domain shifts (e.g., different cells, routes, and weather). The work of Lu et al., published in 2023, is an important first step towa rd developing a deep learning method for estimating SoH using domain adaptation between manufacturers and usage distributions without needing labels for batteries; their results showed that cross-domain learning can help minimize the high costs associated with labeling batteries across their life cycles. A second common theme in the EV literature is estimating SoH from partial load/partial discharge test results, which correspond to the data available from on-board battery management systems (BMS). employed a temporal convolutional neuron network (TCN) on a set of partial discharge profile test results in order to minimize feature extraction and to be able to run on embedded systems Zhang and colleagues introduced an enhanced version of the long short-term memory (LSTM) ensemble model that utilizes random cycling curve segments for its input, addressing uncertainty in real-world charging behavior and improving robustness when appropriate standard cycling curves are not available. Graph-based representations of battery degradation have also been proposed as battery degradation demonstrates structured temporal behavior (or trend) for both cycling and operating conditions. Yao and colleagues created a graph-based state-of-health (SOH) prediction model that represents the relationships between the hea lth indicators extracted from observed data over time, which enhances the ability to learn the degradation trajectories of batteries compared only to those learned via sequential models [34]. Finally, hybrid ML pipelines continue to be of value in cases where interpretability and simplicity of the model are important aspects; Chen and colleagues developed an SOH estimator comprised of an extreme learning machine (ELM) model and utilized a particle swarm optimization (PSO) method to optimize its parameters, where the results demonstrate that "lighter" models optimized appropriately can provide an alternative to comparable accuracy and lower-complexity than other more complex models without using an ELM or PSO.

Recent SOC/SOH studies are increasingly focusing on three gaps that are critical to battery management systems: (i) Physical Consistency (estimates should comply with degradation / state equations) (ii) Data Efficiency (small available labeled data from the lifecycle of a battery) and (iii) Real-world Operating Diversity (e.g. rapid charge, drive cycle variability, temperature range). A strong response to these three critical gaps is the use of physics-informed machine learning. [35].discuss how they propose an approach based on two equations: using physics-informed neural networks to combine physics-based degradation/state relationships and to approximate these using neural networks and thereby produce stable battery degradation models in addition to providing a more precise means of estimating SOH for different battery types and test protocols. Described a State-of-Health (SOH) estimator and its underlying principles as being based on physics-informed neural networks, reinforcing the notion that by embedding physics based constraints, the generalization ability of SOH due to data sparsity/condition changes may be enhanced. In addition to this, they are developing Graph Neural Networks (GNN) to structurally understand the degradation structure of batteries across multiple discharges (battles) and then eliminate the required time-consuming and error-producing process of selecting manual segments. Zhou et al. (2024) proposed an SOH solution using a Graph Convolutional Network (GCN) [36], with systematically selected segments from the discharge voltage curve, which are used to retain the required information about degradation and standardize the training/validation distributions, enabling online SOH estimation based on multiple segments. Zhou et al. (2025) introduced multi-level feature integration for SOH estimation based on actual short working samples, in order to solve the common "messy data" problem seen in electric vehicle fleets as opposed to formally distributed conditions. Finally, integrated physics with representational learning; they used momentum contrast learning along with physics-based learning to create a balanced model for BMS-readyCrepresentation learning models, capable of learning transferable SOH representation while also providing physical plausibility.

3.RESEARCH METHOD

This sort of research employs exclusively AI-based strategies for enhancing estimate accuracy of State of Charge (SOC) and State of Health (SOH) for Electric Vehicle (EV) Battery Management Systems (BMS). Because lithium - ion batteries have nonlinear, time-dependent, and degradation-dependent properties that are impossible to adequately capture using conventional model-based approaches alone, this method depends on data -driven modelling. The study is based on operational battery records, from which validation will be based on actual charge-discharge behaviour, temperature fluctuations, and age-induced battery variations. Several of the major parameters of battery performance, i.e. voltage, electric current, temperature, SOC, and cycle number will be processed systematically through cleaning, normalisation, and feature engineering to ensure that the data provided as inputs into the AI techniques is of the highest possible quality. Variable-length battery cycles will be managed utilising temporal structuring approaches in order to retain deterioration patterns over time.

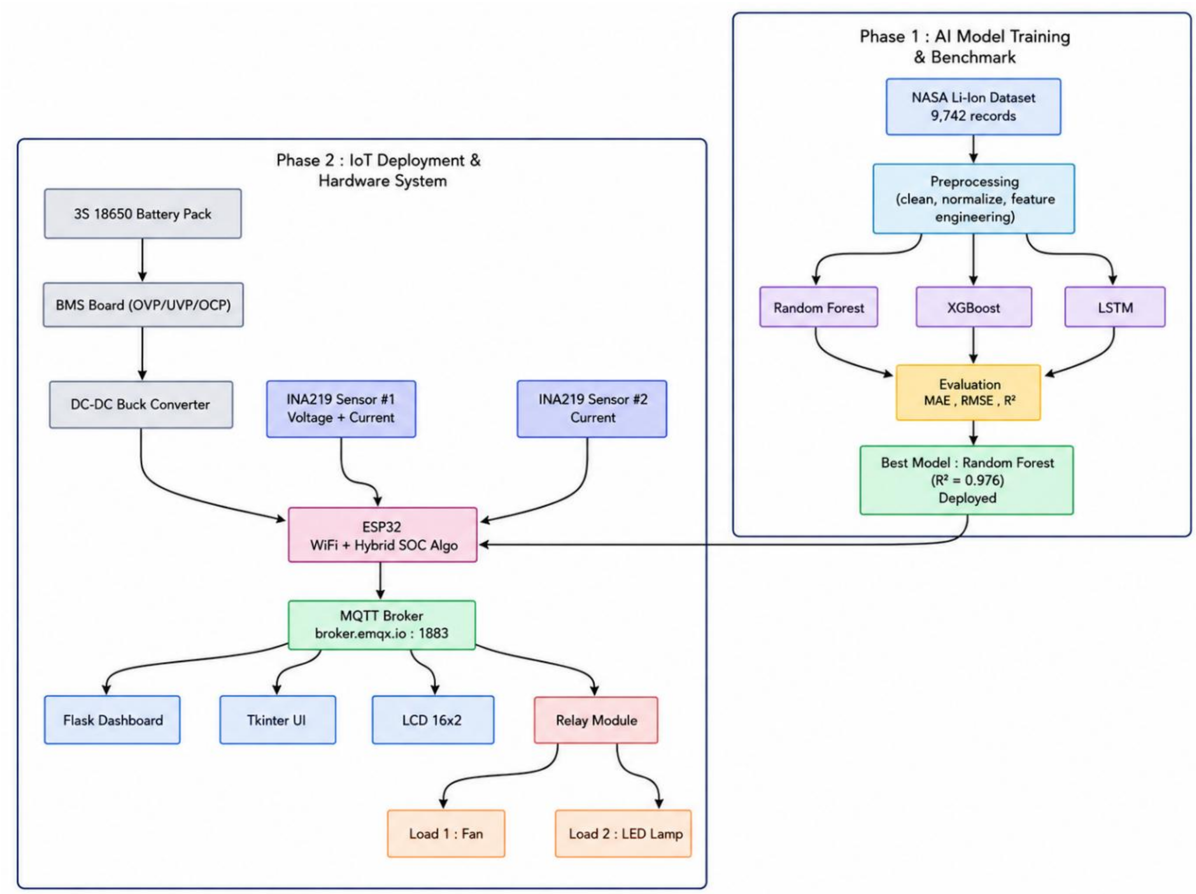

Fig. 2. Research Method

Fig. 2. Combined research framework integrating Phase 1 (AI model training and benchmarking on NASA Li-ion dataset) and Phase 2 (hardware prototype deployment on ESP32 with IoT-based real-time BMS). Phase 1 establishes the comparative AI pipeline — Random Forest (R^2=0.976), XGBoost (R^2=0.951), and LSTM (R^2=0.637) — with feature importance analysis confirming current (0.53) and cycle count (0.30) as dominant predictors. The best - performing Random Forest model is serialised via joblib and deployed to the Flask server in Phase 2, where it drives autonomous relay control over MQTT across 13 topics. The hardware layer integrates dual INA219 sensors (0x40/0x41), a 2-channel active-low relay module (GPIO26/27), JHD 16×2 LCD, and two physical loads (12V fan and LED lamp), with a three-tier voltage protection algorithm operating independently of cloud connectivity. Live experimental validation confirmed V=9.87V, SoC=39.4%, SoH=100%, with LOW VOLTAGE warning correctly triggered.

3.1Research Design

This study uses a quantitative and data-driven approach to research using battery operational data to create Artificial models based on artificial intelligence (AI) to operate battery management systems (BMS). This study employs a dual-mode research design combining quantitative data-driven modelling with experimental hardware validation. In the first phase, standard NASA lithium-ion battery datasets are used to train and benchmark three AI models under controlled, reproducible conditions. In the second pha se, the best-performing model is deployed on an ESP32 microcontroller prototype to validate AI-predicted SOC/SOH values against real sensor measurements from INA219 current sensors, confirming the practical feasibility of embedded ML inference in a physical BMS. Key battery characteristics including voltage, current, and temperature; time, cycle number; and derived variables such as State of Charge (SOC) and State of Health (SOH) are represented as multivariate time-series data. This depiction may be that AI models capture the complexity of non-linear interactions and long-term temporal dynamics that influence battery life and degradation. Because the SOC and SOH are determined by the past usage trends and the overall impact of ageing, the importance of learning in time is evident. Giving estimating capabilities algorithms will be more advantageous in this project than experimental instrumentation to provide more scalable, repeatable and flexible methods to use in future studies to apply to alternative battery chemistries and electric car platforms.

3.2Dataset Selection and Acquisition

An important element of the proposed use of AI-based techniques is the appropriate choice of a technologically sound, validated and frequently used battery dataset so that the accuracy and reproducibility of the resulting results can be maintained. The dataset that will be used in this study is the NASA Lithium -Ion Battery Dataset, as it is publicly available and has had significant use in battery prognostics and health management research. The dataset consists of long-term cycling data of numerous lithium-ion battery cells that have been charged/discharged repeatedly under controlled yet realistic operating conditions. Each battery cell has an initial nominal capacity of approximately 2.0 Ah, and cycling will be continued with each battery cell until a decrease in capacity of approximately 50% is found. The dataset consists of high-resolution time-based measurements for key battery measurements, including terminal voltage (V), load current (A), surface temperature (°C), time (seconds), cycle number, battery identification number, and cycle type (charge/discharge). Back-off temperatures when discharged down to the defined cut-off voltage of 2.7 Volts that represent a realistic operating condition for Lithium-Ion Batteries allows us to investigate in detail how batteries age, their efficiency, and degradation rates over extended periods of operation (e.g., hundreds of charge/discharge cycles). Since the NASA database has established standards for both its structure and completeness, we can efficiently pre-process our data and extract features from the NASA battery-testing dataset and utilize temporal modeling via AI algorithms. Also, we will be able to directly compare the AI models developed in this research to previously published estimates of state-of-charge (SOC) and state-of-health (SOH) methodologies found in the literature utilizing the NASA benchma rk dataset. Therefore, we expect to enhance the scientific rigor and transparency associated with this research.

3.3Data Preprocessing and Cleaning

The noise, conflicts, and insufficient raw battery data generation of incorrect and old records may negatively impact artificial intelligence models. To overcome the above problems, data preparation and cleaning are required to offer data integrity and reliability. They should always operate within the limits of operational constraints (i.e. safe voltage cut-off values) to make sure that the operation and electrochemically feasible nature of the system are adhered to once defective records, batteries with faulty charge/discharge cycles and outliers which may have been brought about by sensor failure are removed. Data normalisation and scaling will be used in all of the input characteristics to create objectively comparable numerical ranges, which are expected to reduce numerical instability and make the convergence process faster across the entire AI training. Mathematical manipulations will be used to generate derived parameters such as cumulative charge, instantaneous power and energy utilised in order to e nhance the overall representational quality of the dataset. These parameters will give information that reflects on underlying battery characteristics which can be utilized as further derivations. Altogether, this preparation step will ensure that the data are correctly organised, provide sufficient information, and can be used in predicting precise and effective SOC and SOH based on AI algorithms and methods to estimate SOC and SOH.

3.4AI Model Development Strategy

This work employs the combination of ensemble machine learning and deep learning methods to construct an artificial intelligence model to properly characterise the difficult, non-linear performance of lithium-ion batteries in electric cars. Random Forest and XG-Boost ensemble regression models are selected because they are able to deliver accurate predictions, are resilient against noise and are less prone to overfitting. The random forests and XG-Boost models will learn the nonlinear correlations between the major battery variables such as voltage, current, temperature, state of charge and cycle number, and will thus be suitable for predicting SOC and estimating energy loss. The long short-term memory (LSTM) neural networks will be used to represent the temporal relationships of the battery cycle data. LSTMs have the capacity to learn from time series data and will be able to recognise long-term deterioration patterns, which are crucial for accurate SOH calculation. The synergistic combination of ensemble learning and deep learning will allow for a complete, comparative investigation of model performance, generalisation and computing efficienc y, leading to the selection of viable AI approaches for intelligent battery management systems.

3.5Model Training and Validation

Training and evaluating an Artificial Intelligence (AI)-based Model throughout its construction is a key component of constructing accurate models for predicting State of Charge (SOC) and State of Health (SOH) of batteries in Electric Vehicle Battery Management Systems. For this study, an AI model was trained using 80% of a processed dataset of 9,742 records, and the model's performance was independently assessed using the remaining 20%. This method of dataset splitting reduced the likelihood of model overfitting and allowed models to be assessed without testing their quality or capacity to generalise to the training dataset. For training AI models, supervised learning approaches were utilised where input characteristics (e.g., voltage, current, temperature, state of charge, and cycle number) are mapped to output variables (e.g., SOC, SOH, and net energy loss). Model hyperparameters were optimised by iterative tuning with the objective to offer the Model with least predicted error and to give the Model with e nhanced convergence during the training stages. All models were implemented in Python 3.10 using scikit-learn 1.3 (Random Forest, XG-Boost via XG-boost 1.7) and TensorFlow 2.12 (LSTM). Hyperparameters were selected via grid search with 5 -fold cross-validation on the training split (random state=42 throughout). The final configurations are documented in Table 2 to ensure full reproducibility.

Table 1: Final Model Hyperparameters

Framework	scikit-learn 1.3	XGboost 1.7	TensorFlow 2.12 / Keras
Estimators / Epochs	100 trees	200 boosting rounds	50 epochs
Max Depth	None (unlimited)	6	N/A
Learning Rate	N/A	0.1	0.001 (Adam)
Min Samples Split	2	N/A	N/A
LSTM Units	N/A	N/A	64 units, 2 layers
Dropout Rate	N/A	N/A	0.2
Batch Size	N/A	N/A	32
Time Steps (lookback)	N/A	N/A	10 steps
Train/Test Split	80% / 20%	80% / 20%	80% / 20%
Random Seed	42	42	42
Input Features	5 (V, I, T, SoC, Cycle)	5 (V, I, T, SoC, Cycle)	5 × 10 timesteps
Validation Method	5-fold cross-validation	5-fold cross-validation	Hold-out val (10%)
Inference Hardware	ESP32 (via Flask/MQTT)	Flask server only	Not deployed

The performance of each Model will be quantitatively evaluated based on three standard statistical measures. The Mean Absolute Error (MAE) represents the average magnitude of the prediction error as defined by

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (1)$$

Where yi and ŷi represent the actual and predicted values, respectively, and N is the total number of samples. The Root Mean Square Error (RMSE), which penalizes larger errors more severely, is expressed as

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (2)$$

Additionally, the coefficient of determination (R^2) evaluates the proportion of variance explained by the model and is given by

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (3)$$

Where $\bar{y}$ denotes the mean of observed values.

The models are also enhanced using cross-validation techniques to train and test them on other data sources to enhance the robustness of the models. Cross-validation will assist in reducing the level of variability in the predictions and the reliance of the predictions in a new environment, as systematic model training and validation based on the rules of data will be carried out. Consequently, the AI models will have been trained via a statistically sound approach such that they will deliver consistent, precise, and realistic outputs in the context of real-life applications of BMS.

3.6Comparative Performance Analysis

A detailed comparison performance analysis is conducted in the comparison of the two electric vehicle battery management systems to find out the best proximity of Artificial State of Charge (SOC) and State of Health (SOH) estimates. Perhaps, the common intelligence model can exist between these two systems. The metrics of the performance that were used to compare a range of A.I. based models were the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of Determination (R2) which charact erize the performance of a prediction, stability and robustness of each model. In addition to the analysis of errors, the important points which determine Energy Loss and Battery Degradation were investigated using the Feature Importance Metrics such as Current; Voltage; Temperature; SOC; and Cycle. When comparing the performance of the various AI Models, it is evident that there is a level of stability and reliability in an ensemble learning method (e.g., Random Forest; XGBoost) that is of much higher order than that of deep learning method (e.g., Artificial Neural Networks). This is likely to be related to their ability to capture nonlinear associations and minimize overfitting, and also their inherent biases because of the time nature of data in the particular batches of data of the particular battery. All in all, the insights of the

assessment can serve as a convenient reference point of information on which the nature of AI model can be deemed as the most effective to apply to a real-life battery management system (BMS).

4.HARDWARE PROTOTYPE IMPLEMENTATION

4.1System Architecture Overview

The BMS framework is an AI-based framework, which was designed and experimented under experimental conditions through the design of a complete hardware prototype and its assembly and testing under the real operating condition.

It has four functional layers: (i) the energy source layer, comprising a 3S ICR-18650 lithium-ion battery pack, fastened by a 20A BMS board; (ii) the sensing layer, which has two Adafruit INA219 current voltage sensor on the I2C bus;

(iii) the intelligence and control layer, which incorporates an ESP32 micro

4.2Component Specifications

Table 2: Detailed Component Specifications of the Proposed AI-Based Battery Management System

Component	Model / Specification	Function in BMS	Interface
Microcontroller	ESP32 (240 MHz, dual-core, Wi-Fi)	AI inference, MQTT, relay control, SOC calculation	Wi-Fi / I²C / GPI O
Battery Pack	3S ICR-18650, 2500mAh, 11.1V nominal, 12.6V max	Energy source under test	Direct connection

BMS Protection Board	3S 20A Li-ion protection board	OVP, UVP, OCP, short-circuit protection	Series with pack
Current Sensor 1	INA219 (I²C addr: 0x40), 0.1Ω shunt, 16V/400mA	Load 1 current + battery voltage measurement	I²C (SDA/SCL)
Current Sensor 2	INA219 (I²C addr: 0x41), 0.1Ω shunt, 16V/400mA	Load 2 current measurement	I²C (SDA/SCL)
Relay Module	2-channel, 5V coil, active-low logic, GPIO26/GPIO27	Autonomous load switching based on ML output	Digital GPIO
LCD Display	JHD 162A, 16×2, I²C backpack (0x27)	Local V, SoC, SoH, cycle, relay status display	I²C
DC-DC Converter	Buck converter (adjustable), STONE-PRO 12V fan	Voltage adjustment, thermal management load	PWR rail
Web Dashboard	Flask + Flask-SocketIO, Python 3.x, 127.0.0.1:5000	Real-time remote monitoring + relay control	WebSocket/HTTP
Desktop UI	Tkinter + paho-mqtt, Python 3.x	Alternative monitoring + relay toggle	MQTT
ML Model	RandomForestClassifier (scikit-learn, n=100 trees)	Voltage→Decision classification (4 classes)	Embedded inference
MQTT Broker	broker.emqx.io:1883, 13 topics	Publish sensor data, subscribe relay control	TCP/IP WiFi

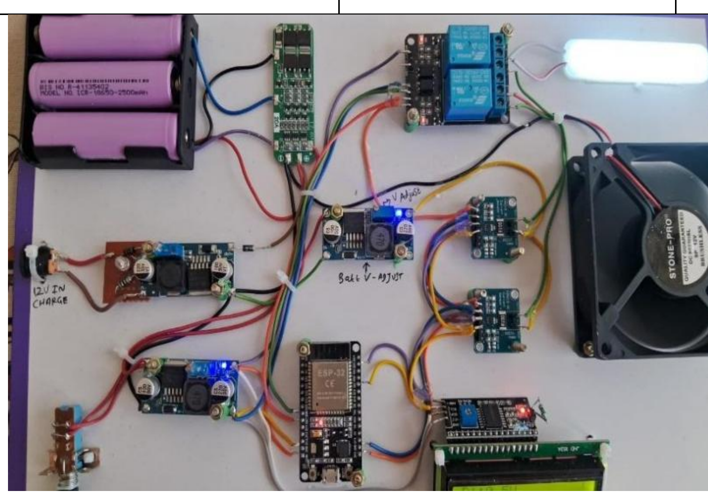

Fig. 3. Photograph of the complete AI-BMS hardware prototype.

Figure 3. shows the constructed hardware prototype that was created to experimentally test the proposed AI - based BMS framework. The system is built on a flat insulated board to enable easy identification of components and interconnection. The main source of energy is the 3S ICR-18650 lithium-ion battery pack (nominal 11.1V, maximum

12.6V, 2500mAh), which is connected to the 20A BMS protection board, which offers hardware -level over-voltage, under-voltage, and over-current safety regardless of the software control la yer. The battery output voltage is scaled and stabilised with two adjustable DC-DC buck converters to the sensing and control circuits, with the Battery V-Adjust label showing the path of primary voltage regulation. The ESP32 microcontroller, which is in t he middle, acts as the intelligence node - reading I 2C data on both INA219 sensors, running the hybrid SOC algorithm, broadcasting MQTT telemetry, and asserting relay control signals. The two INA219 modules (R100 shunt resistors, visible with green standoffs) measure currents of each load with 1mA resolution. The 2 channel relay module (right -centre) galvanically isolates the ESP32 logic-level signals and the battery load circuit. Load 1 and Load 2 are a 12V brushless fan (STONE-PRO, bottom-centre) and an LED lamp (bottom-right, visibly illuminated), respectively, and can be used to illustrate the real power switching under AI-controlled switching.

4.3Embedded SOC Algorithm (Hybrid Method)

The ESP32 uses a hybrid SOC estimation algorithm between Coulomb counting and voltage -based mapping as the definition in Equation (4) and Equation (5). INA219 (bus voltage + shunt voltage) is used to sample the battery voltage at 500ms intervals. SOC can be calculated as a weighted average:

SOC_voltage = ((V_meas - V_min) / (V_max - V_min)) × 100 ... (4) SOC_hybrid = (0.4 × SOC_voltage) + (0.6 × SOC_coulomb) ... (5)

Where V_min = 10.8V (0% SOC), V_max = 12.6V (100% SOC) for the 3S pack. The number of coulombs is reduced at a rate of 500ms with total load current (I L 1 + I L 2). SOH decays by 0.1 percent per energy cycle completed, and has a basement at 80 percent.

4.4ML-Based Autonomous Load Control

The trained Random Forest classifier (see Section 3.5) is deployed on the server in Flask application. After every voltage MQTT message, the Flask server asks the model to predict optimal load setting (Decision: 0=Both ON, 1=Load1 ON/Load2 OFF, 2=Load1 OFF/Load2 ON, 3=Both OFF) and publishes relay control commands to the ESP32 via MQTT. The ESP32 turns on and off a relay with active-low (LOW=ON, HIGH=OFF) logic on GPIO26 (Relay1) and GPIO27 (Relay2).

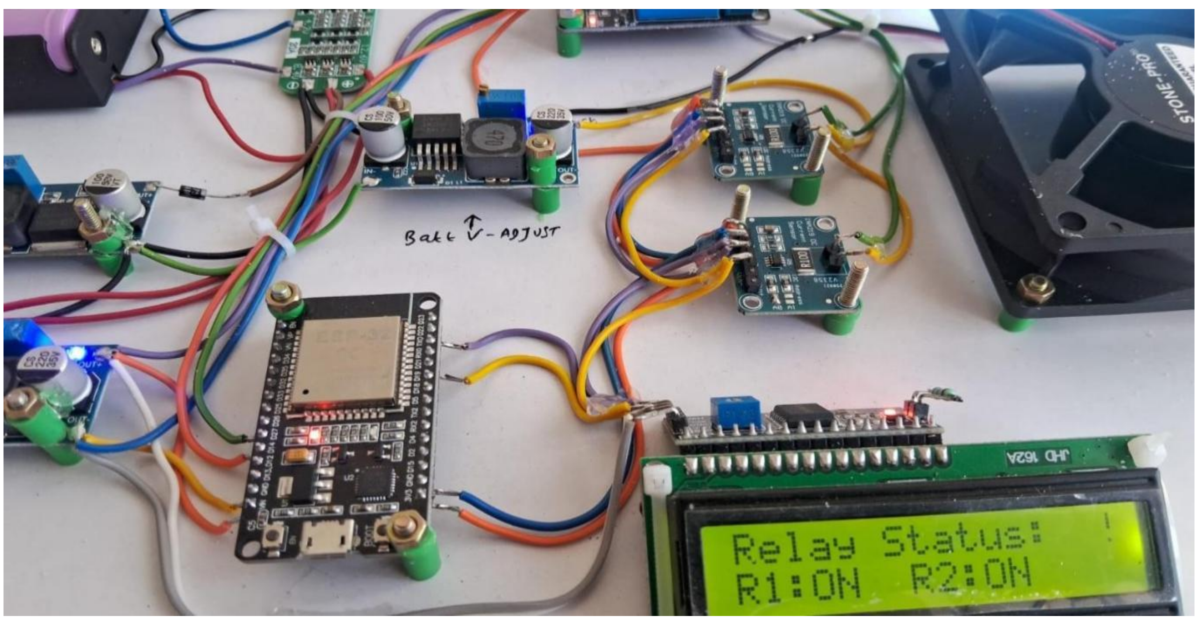

Fig. 4. LCD display output in DISPLAY_MODE_RELAY_STATUS showing R1:ON R2:ON — both loads active simultaneously.

The system under full-load operating condition is shown in Fig. 4 which according to the ML classifier, the Decision Class 0 (Both Loads ON) has been made since the measured battery voltage has reached a voltage higher than 10 V. The LCD display (JHD 16×2 LCD display) with DISPLAY_MODE set to DISPLAY_MODE_RELAY_STAT US (one of four rotating display modes to rotate every 3 seconds as implemented in the ESP32 firmware) confirms that both Relay 1 (R1:ON) and Relay 2 (R2:ON) are connected, meaning both the fan load and LED load This is the highest charge of the battery in the experiment, when there are sufficient energy reserves to enable the delivery of the maximum amount of simultaneous loads, without the high risk of accelerated degradation.

4.5Staged Voltage Protection Logic

In addition to ML-based load control, the ESP32 implements a three-tier hardware protection algorithm independent of the cloud connection:

Table 3: Three-Tier Hardware Protection Strategy for Battery Safety in Proposed BMS

Tier	**Voltage Threshold**	**Action**	**MQTT Warning Published**
Tier 1 — Warning	9.0V < V < 10.0V	Warning message displayed on LCD; MQTT warning published	"Warning: Battery Low! < 10.0V"
Tier 2 — Load Shed	8.0V < V < 9.0V	Relay 1 OFF command issued; Load 2 continues	"Warning: Battery Low! < 9.0V"
Tier 3 — Emergency	V ≤ 8.0V	Both Relay 1 and Relay 2 forced OFF (GPIO HIGH)	"EMERGENCY SHUTDOWN: Battery critically low!"

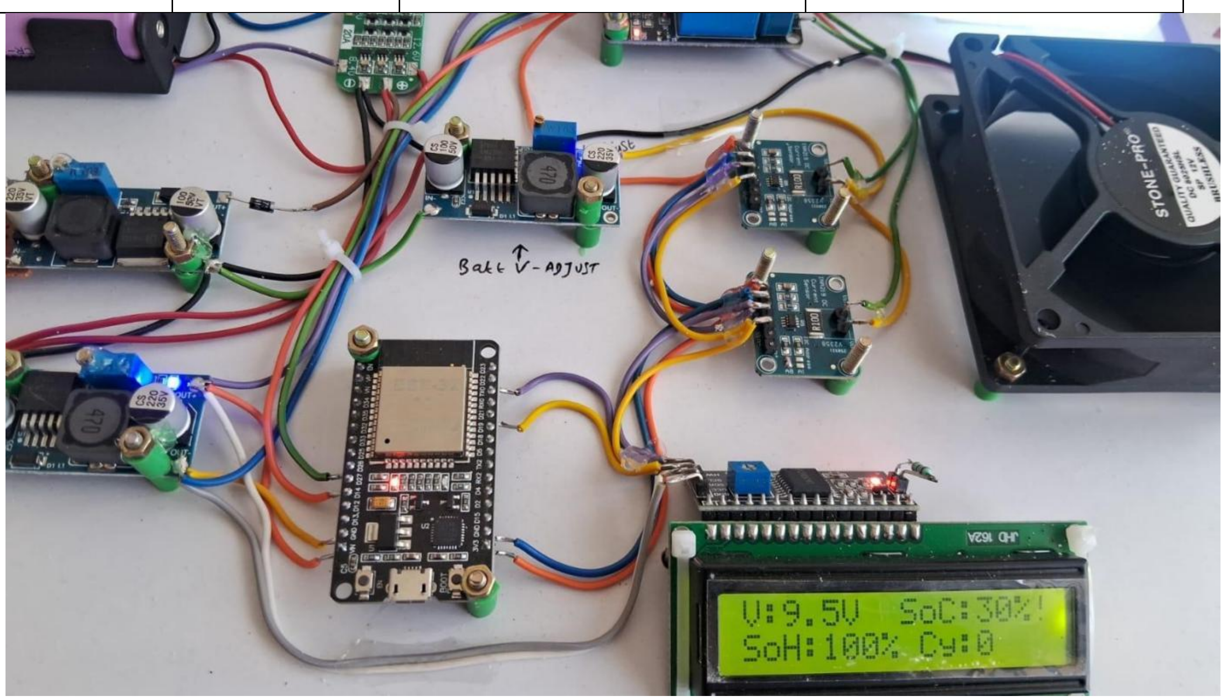

Fig. 5. Battery Management System Under Critical Operating Condition with Multi-Channel Alerts and Hybrid SOC Algorithm Display

Figure 5 shows a critical operating condition which was captured during experimental discharge test. The LCD shows a terminal voltage of 9.5V where the hybrid SOC algorithm calculates a State of Charge of 30% and the State of Health is at 100% because no full charge-discha rge cycle (Cycle count = 0) has been done to activate the 0.1% degradation SoH decrement. Importantly, the character of the LCD that is displayed in the upper-right corner (positional character 15, row 0) as an exclamation mark is programm atically enabled by the checkBatteryProtection() function when the length of the warning message is greater than 0, i.e. the Tier 1 voltage threshold (V < 10.0V) has been violated. With this level of voltage, the system has emitted a MQTT warns message (Wa rning: Battery Low! < 10.0 V) to the bms/system/warning topic, which has also been updated in the Flask web Dashboard (LOW VOLTAGE-Battery critical!) and in the Tkinter desktop status panel. Layered safety communication architecture of the proposed system is on display in this multi-channel concurrent alerting LCD local display, MQTT broker publication, web dashboard banner and desktop UI log. The 30% SOC at 9.5V is in line with the SOC mapping with the voltage (V_min=10.8V, V_max=12.6V) weighted at 40 per cent along with the Coulomb counting component, which confirms the continuity of the hybrid estimation algorithm across the mid-to-low discharge region.

4.6IoT Communication Architecture — MQTT Topic Map

The sensor data are sent to the public EMQX MQTT broker (broker.emqx.io:1883) via WiFi SSID (MyIOTdevice). The ESP32 broadcasts 11 sensor/status messages every 2 seconds and subscribes to 2 control messages to activate relays. Total: 13 live MQTT topics.

Table 4: MQTT Topic Structure and Data Exchange Specifications for Proposed BMS

MQTT Topic	Direction	Data Type	Update Rate
bms/battery/voltage	ESP32 → Broker	Float (V)	2 sec
bms/battery/soc	ESP32 → Broker	Float (%)	2 sec
bms/battery/soh	ESP32 → Broker	Float (%)	2 sec
bms/load1/current	ESP32 → Broker	Float (A)	2 sec
bms/load1/power	ESP32 → Broker	Float (W)	2 sec
bms/load2/current	ESP32 → Broker	Float (A)	2 sec
bms/load2/power	ESP32 → Broker	Float (W)	2 sec
bms/relay1/status	ESP32 → Broker	String (ON/OFF)	On change
bms/relay2/status	ESP32 → Broker	String (ON/OFF)	On change
bms/system/status	ESP32 → Broker	String (Online/Offline)	On connect
bms/system/warning	ESP32 → Broker	String	On threshold trigger
bms/relay1/control	Dashboard → ESP32	String (ON/OFF)	On user command
bms/relay2/control	Dashboard → ESP32	String (ON/OFF)	On user command

5.RESULTS AND DISCUSSION

This section summarises the results of a few experimental and artificial intelligence (AI)-based techniques to improve predictions of State of Charge (SOC), State of Health (SOH) and energy losses in Electric Vehicle (EV) Battery Management Systems (BMS). These findings are the outcome of the massive data processing, feature extraction and modelling with NASA battery data, and then three approaches (Long Short-Term Memory (LSTM) networks, Random Forest and XGBoost) are compared. The Mean Absolute Error (MAE), root square error (RMSE), and coefficient of determination (R 2) are employed to evaluate the ability of the three algorithms to predict the SOC, SOH and net energy loss of the models. Most of the numerical results are always presented in graphical illustrations of SOC profiles, scatter plots of SOH predictions, and estimated values of net energy loss. These are also used to establish at other angles the extent to which each model portrays the same performance under other conditions of operation. The au thors can provide more accurate representation of the nonlinear characteristics of deterioration of batteries and provide less predicted error by supporting ensemble learning methods, especially the Random Forest. The sensitivity of some of the main inputs that are utilized in the generation of energy loss forecasts such as current, number of cycles, and State of Charge (SOC) to the general effectiveness of the energy loss forecasts is also well analyzed. The results show that Artificial Intelligence systems offer an advantage over traditional methods of assessing the performance of batteries and offer an implication of the practical application of real-time BMS, battery safety and optimisation of battery life to be used in electric cars.

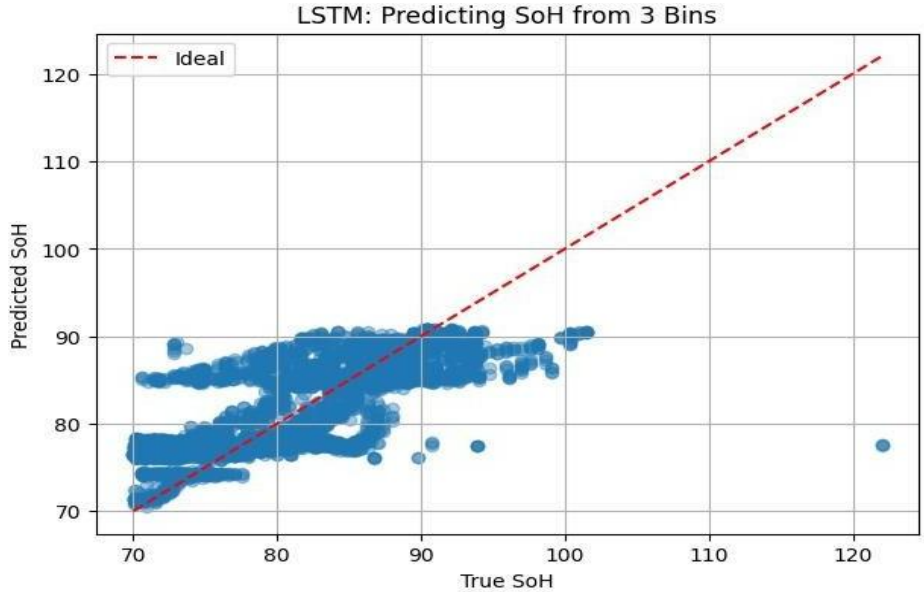

Fig. 6. LSTM: Predicting SoH from 3 Bins

The LSTM model achieves only fair results when predicting State of Health (SoH) based on 3 -bin averaged data as compared to real SoH. The majority of the predictions, as one can observe, lie within the 75 percent and 90 percent SoH range; the actual SoH predictions lie within the ranges of about 70 percent and 100 percent with some very high predictions of SoH being above 120. These high SoH forecasts are likely to be due to either outliers or noise in the dataset. The model performance necessary to estimate SoH values appropriately portrays a strong deviation of the ideal reference line as the SoH level increases and has little sensitivity to deterioration patterns. The performance of the LSTM model is similar to the Phase-2 results where it was found that the Random Forest model had a better model performance (R 2 = 0.976) compared to the LSTM model (R 2 = 0.637; higher MAE and RMSE). The small size of the dataset and the insufficient sequential depth of the input data cripples the LSTM in its capacity to learn longer patterns of deterioration.

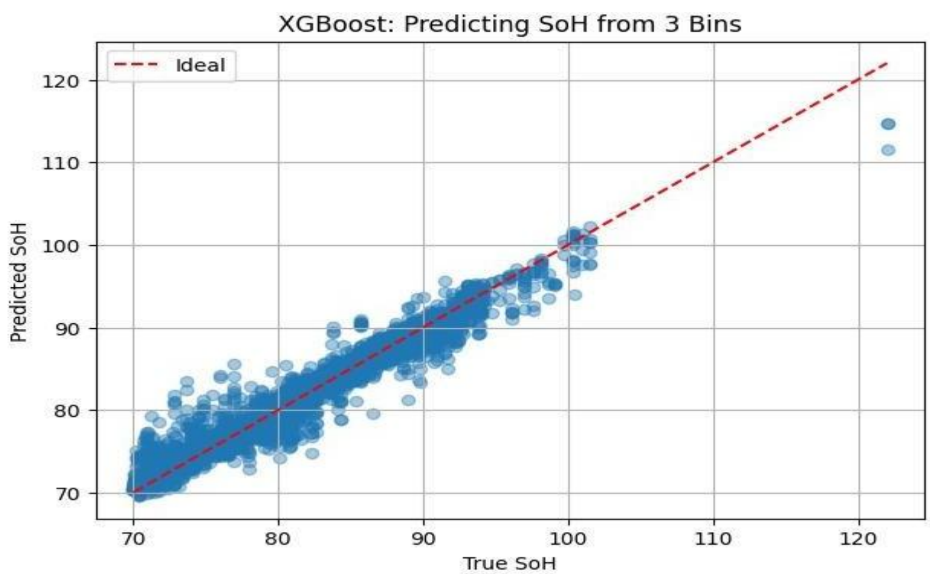

Fig. 7. XGBoost: Predicting SoH from 3 Bins

The findings of the State of Health (SoH) prediction utilising 3 -bin average data and an XGBoost-based model closely match the actual SoH values. The bulk of the data points form a linearity similar to an ideal reference line and generally lie within the SoH range of 70%–100%. The data reveals that the model can reliably forecast SoH values, and a lso that the model has been able to understand the nonlinear deterioration patterns included in the data. There is considerable fluctuation in the data, notably for SoH levels over 100%, suggesting that there may be somewhat increased uncertainty when forecasting extreme instances. In comparison to LSTM, XGBoost demonstrated a strong predictive accuracy of $R^2 = 0.951$ and a comparable degree of predictive accuracy fo r prediction errors (MAE and RMSE). These results corroborate the findings of the Phase-2 report, which demonstrated that XGBoost-based techniques offered a more robust approach to estimating SoH than LSTM models. The study's findings therefore confirm that a prediction model based on XGBoost may be utilised to accurately track the health of EV batteries.

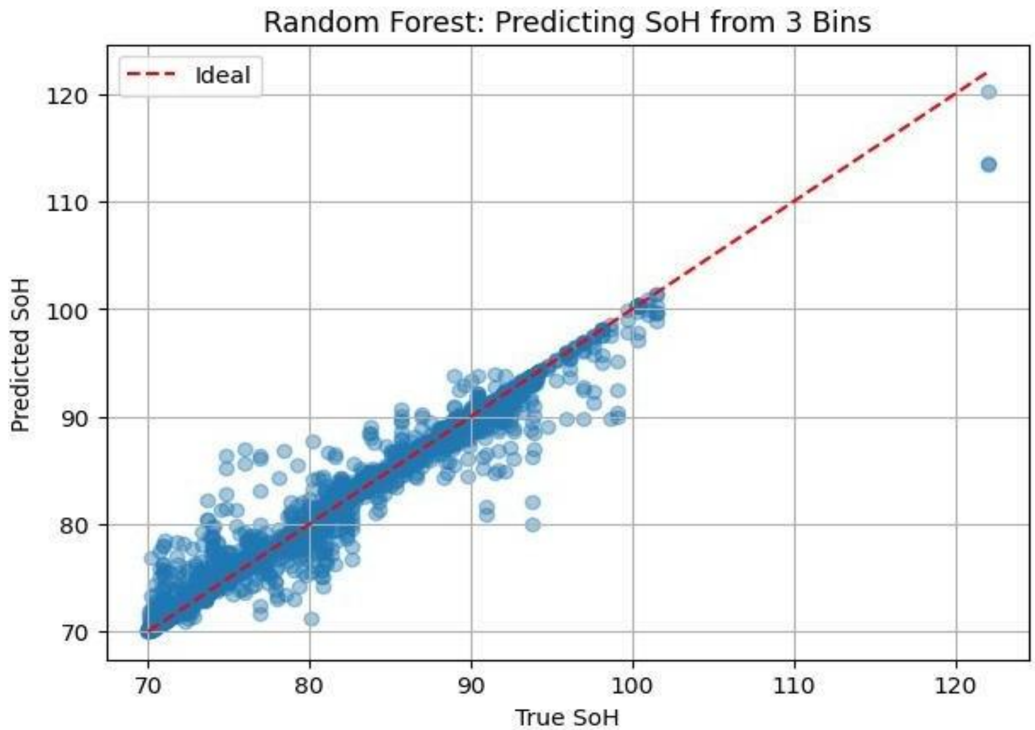

Fig. 8. Random Forest: Predicting SoH from 3 Bins

The predictions of State of health (SoH) made by the Random Forest model based on 3 -bin averaged data show the nearest concurrence with the real SoH values, compared to the other two models considered. Almost all of the data lines converge well around the ideal reference line throughout the entire SoH range of 70%-100% of the battery life cycle, which is indicative of the better representation of nonlinear battery degradation by the model. Even at SoH extremes there is minimal scattering which is consistent with the quantitative results (R 2=0.976, minimum MAE and RMSE), and which proves that in this case, Random Forest is the best and most credible estimator.

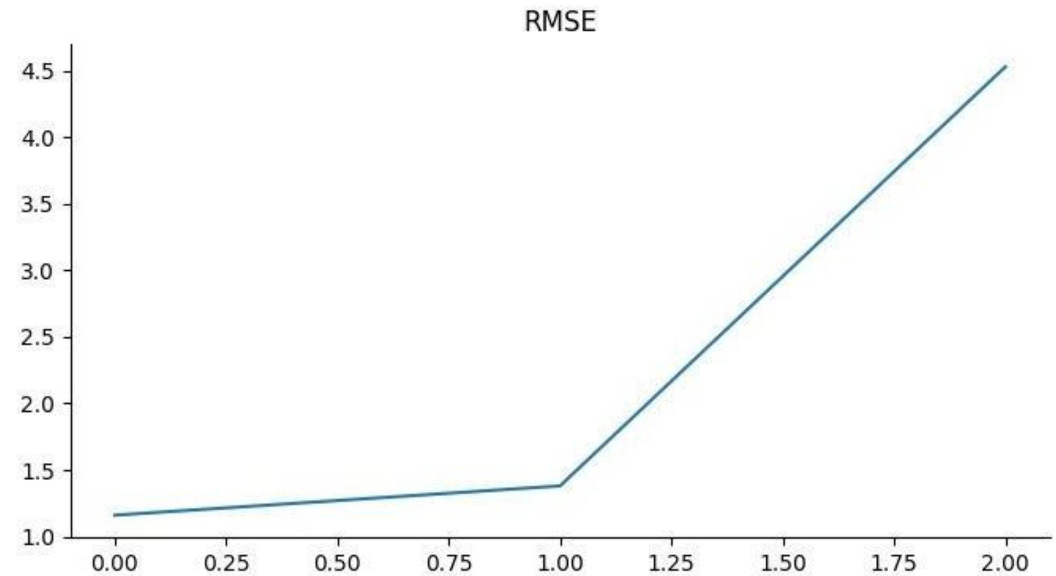

Fig. 9. RMSE vs. Independent Variable

Figure 9 illustrates a change in the model's prediction accuracy when the RMSE fluctuates in tandem with changes in the independent variable. While the model produces very accurate predictions (i.e., low RMSE) within the lower portion of this range (1.1 to 1.4), the RMSE increases rapidly after the independent variable's value reaches 1.0 into the 3.0 to 4.5 range, denoting that there is poor prediction accuracy produced by the model at or above 1.0. The RMSE's quick growth implies that the model is having difficulties generalising to severe situations, which might occur either because of a lack of data, nonlinearity, or restricted model capabilities. Therefore, additional improvement of the model, with an emphasis on using training data at or above this threshold, is necessary to ensure the model produces reliable results as operating conditions move away from normal operational ranges.

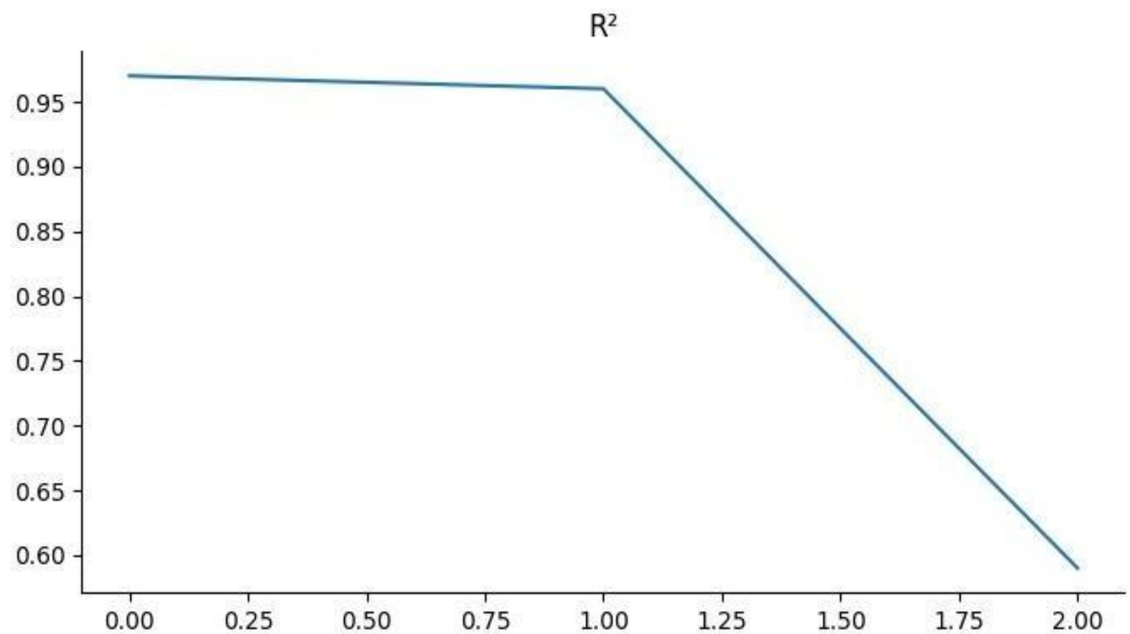

Fig. 10. R^2 vs Independent Variable

The trend for the Coefficient of Determination (R^2) model determined through Operation Conditions (as illustrated in Figure 10) provides useful information regarding the explanatory power of the model. The initial R^2 value is approximately 0.96–0.97 meaning that 96–97% of the variability in the data can be explained by the model making it highly reliable to use for predictive purposes. R^2 falls abruptly to approximately 0.59 past an independent variable value of 1.0 indicating significant loss of predictive effectiveness at higher operating ranges typically due to increased non-linearity, a higher prevalence of data imbalance, and/or insufficient training samples. These trends suggest that adaptive modeling and/or segmented training strategies need to be implemented to achieve high levels of predictive accuracy over the entire range of operating conditions.

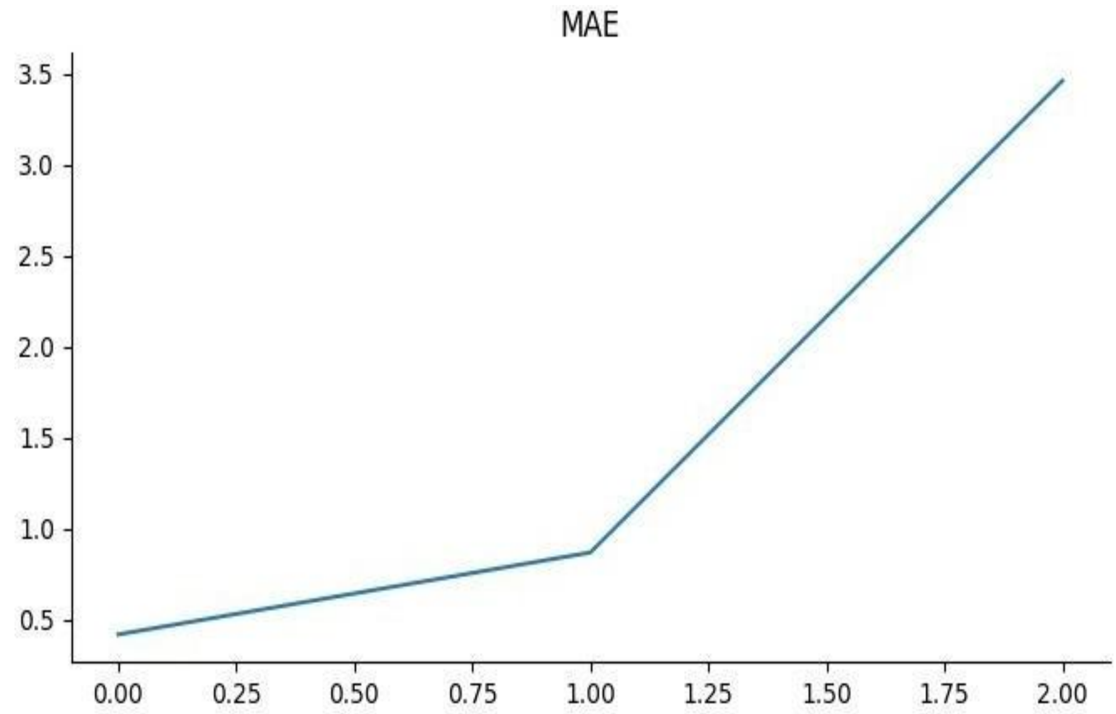

Fig. 11. MAE (Mean Absolute Error)

The Mean Absolute Error (MAE) variation shown in Fig. 11 is an indicator of how accurately the model can predict performance under different operating scenarios. When the independent variable is at lower levels of resolution, there is little change in the MAE and it will increase steadily from ~0.45 -0.9. This demonstrates a generally consistent and accurate predictive ability of the model. However, once the independent variable exceeds a level of 1.0, there is a very dramatic increase in MAE that approaches ~3.5, which indicates a large increase in prediction error. This rapid increase in prediction error shows that the model has lower levels of robustness at higher operating levels and could result from battery behavior that does not exhibit linear characteristics, the lack of good training data, or the model being over fitted to the training dataset. This trend demonstrates the need for improved training techniques or adaptive modeling so that consistent accuracy can be maintained across all operating conditions.

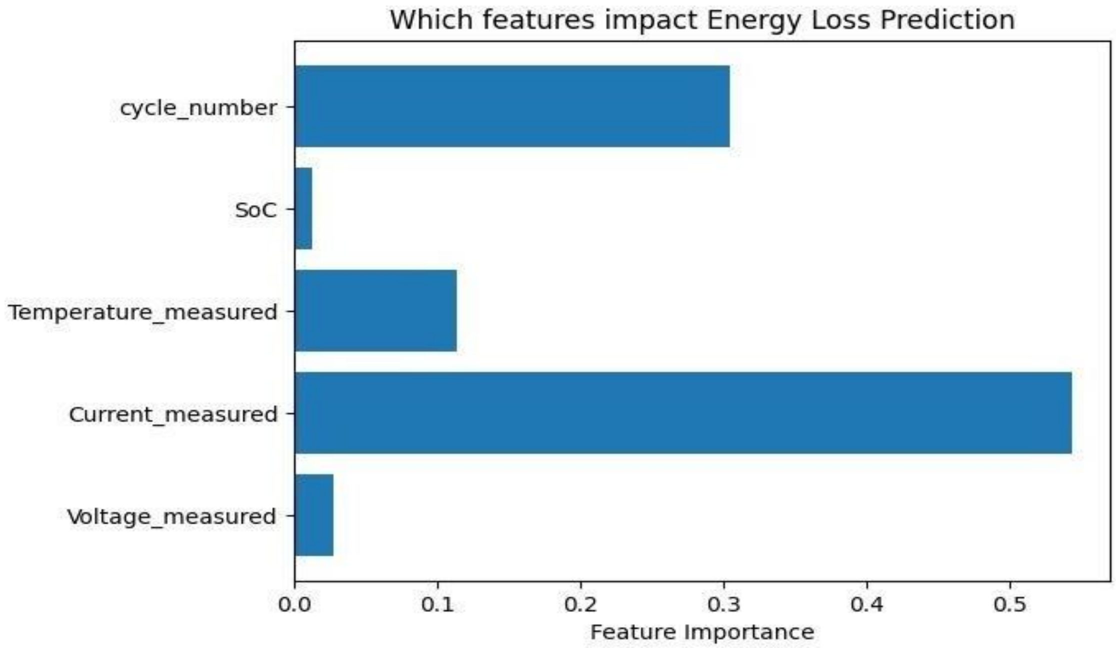

Fig. 12. Features Impact Energy Loss Prediction

Figure 12 illustrates both importance of features affecting predictions of net energy losses. The ranked ordered pile of weights shows that the current measured has the highest weight contributing 0.53 on an overall scale of 0 -1; followed by usage cycle number which weighs approximately 0.30 indicating how battery age and history affect the amount of energy loss. Temperature also has some level of significance at roughly a 12% contribution (≈.12%), accruing due to indirect thermal effects caused by degradation during charge and discharge (use) processes. In contrast, state-of-charge (SOC) and measured voltage contribute very little, weighing approximately 0.04, demonstrating that SOC and voltage have lower direct/primary correlations with predicting energy losses. Current and cycling patterns are the two biggest contributors driving energy loss in EV batteries providing critical information when utilizing Artificial Intelligence - assisted Battery Management Systems.

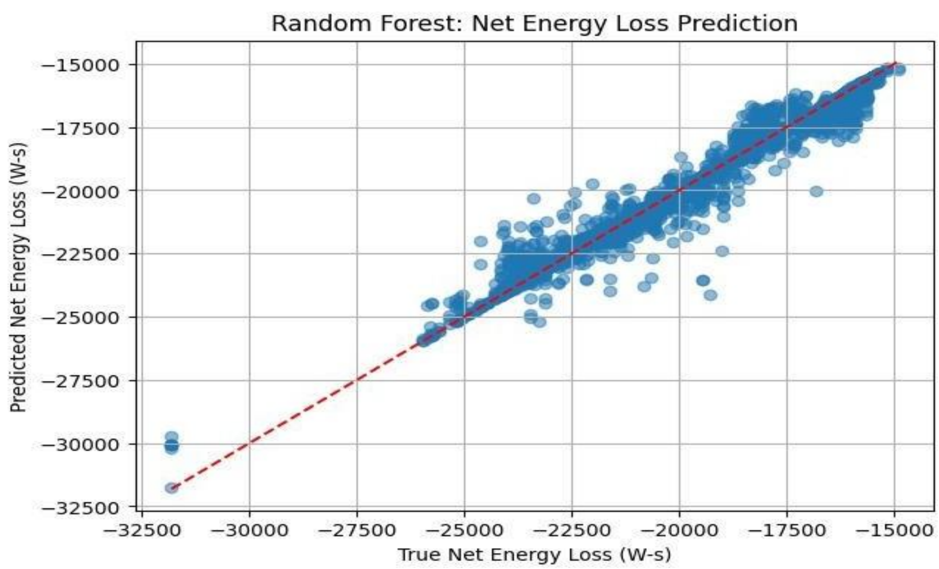

Fig. 13. Random Forest: Net Energy Loss Prediction

According to the Random Forest scatter plot shown in Fig. 13, the relationship between the predicted and actual net energy losses (W·s) demonstrates a clear linear correlation; furthermore, the percentages of the individual points plotted on or near the ideal % line shows that most all of them are located very close to this line. Ne t energy losses were found to occur between about −32,000 W·s and −15,000 W·s, with little spread exhibited by predicted values; thus, providing evidence of accurate prediction ability. Additionally, very few outliers can be found when examining both ends of this spectrum; these points can be accounted for as small differences in energy losses that exist during extreme operating conditions. These results agree with those found within the quantitative data (R^2=0.976, lowest MAE and RMSE), thus corroborating the use of Random Forest methodology as a reliable and accurate tool providing estimates for energy losses within Artificial Intelligence based EV Battery Management Systems

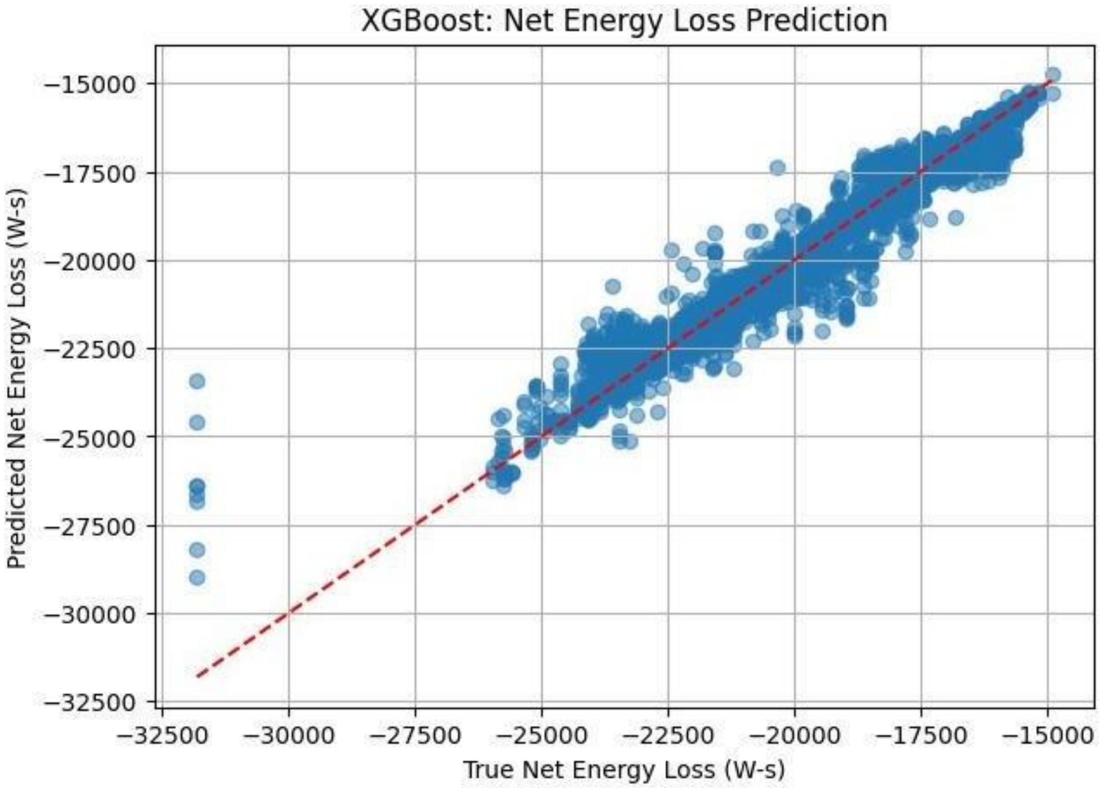

Fig. 14. XGBoost: Net Energy Loss Prediction

XGBoost effectiveness as a reliable estimator of energy losses for AI-enabled EV Battery Management Systems has been validated through quantitative performance metrics as indicated by the figures presented in the scatter plot in Fig

14. The net energy loss prediction W·s had a strong, positive linear correlation with measured values. The estimated values were clustered about the ideal line throughout almost the entire range of net energy loss (-32000 W·s to -15000 W·s) with a slightly larger degree of dispersity than that observed in the Random Forest model within lower net energy losses, indicating a higher degree of vulnerability by the XGBoost algorithm to predicting accurately under extreme conditions. The degree of clustering around the ideal line, however, is indicative of the model's strong predictive capability. The XGBoost model proved to have a very high R2 (0.951), moderate MAE and RMSE and, therefore is an accurate, reliable estimator of energy losses for AI-enabled EV Battery Management Systems.

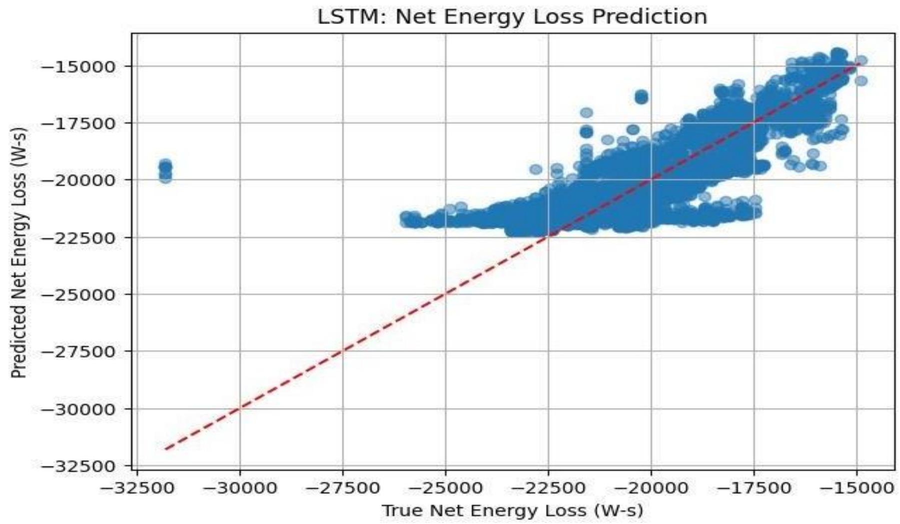

Fig. 15. LSTM: Net Energy Loss Prediction

Figure 15 presents a scatter plot demonstrating the performance of the LSTM model with respect to predicted versus true values of net energy (in W·s). In general, there is a positive correlation between the predicted values and the true values; however, there is a much greater amount of dispersion among the data points relative to the ideal reference line compared to Random Forest and XGBoost models. The observed range of true net energy loss was approximately −32,000 W·s to −15,000 W·s; however, the predicted losses using the LSTM model clustered in a narrower band, indicating an underestimation at higher magnitudes of loss and poor sensitivity to extreme values. The lack of generalization and low accuracy of predictions for very severe operating conditions are demonstrated in the quantitative results, where the LSTM model produced the lowest R^2 value (≈ 0.637) and highest MAE and RMSE indicating it provided the poorest prediction for energy loss using the dataset at hand.

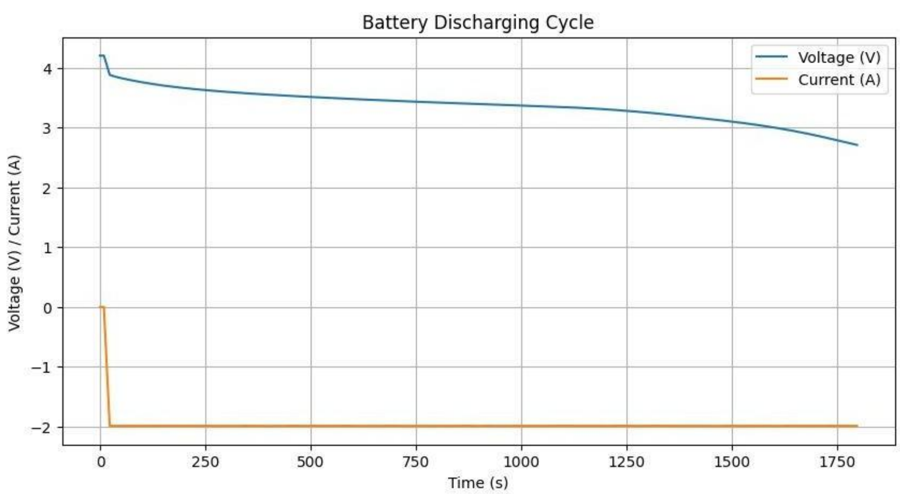

Fig. 16. Battery Discharging Cycle

The discharge characteristics of a lithium-ion battery show steady and consistent lithium-ion characteristics (a typical lithium-ion battery discharging characteristic). Initially, the voltage lowers from around 4.2 volts down to 3.9 volts, mostly owing to the surface charge effect. Following this initial surface charge impact, the voltage gradually drops during a discharge period of around 1800 seconds (30 minutes) to roughly 2.8 volts. Throughout the discharge process (as seen in figure 16), the current stays almost constant at −2 amperes, demonstrating that the discharge process is under regulated constant-current discharge conditions. Assurance that the battery is operating properly and that there are no sudden changes in operation (i.e., no steady-state circumstances occur) within the experimental dataset is provided by the steady current profile and smooth voltage drop, which validates the integrity of the experimental dataset. By using AI-based battery modelling technology, such discharge activity offers a strong basis for precisely modelling the state-of-charge, state-of-health, and energy loss of the AI-enabled Battery Management System.

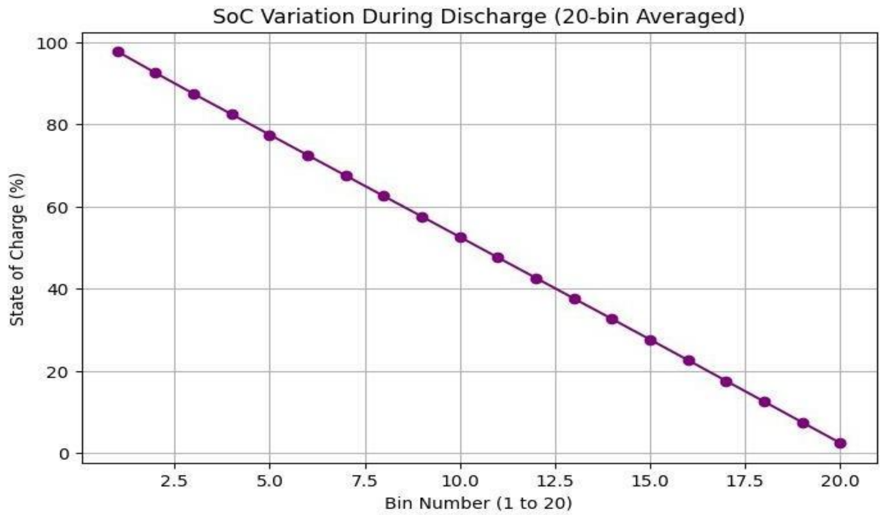

Fig. 17. State of Charge (SoC) Variation during Discharge (20-bin Averaged)

The SoC data results in a linear and normalized downward trend from 98% to 2% (with respect to the value of the bin number [1-20]) and provides an indication of the uniformity of the discharge process, in that there are no sudden jumps (fluctuations) in SoC, indicating consistency in battery discharge and energy use. The linear reduction in SoC, illustrated in Figure 17, confirms that the bin-averaging and Coulomb counting calculations that were used to process the dataset generated an accurate representation of the discharge characteristics of the dataset and were essential for accurately modelling the SOC of the batteries in the dataset. This reliable discharge characteristic confirms that the dataset is worthy of use with AI models in developing algorithm s for SOH and SOC estimation within electric vehicle Battery Management Systems.

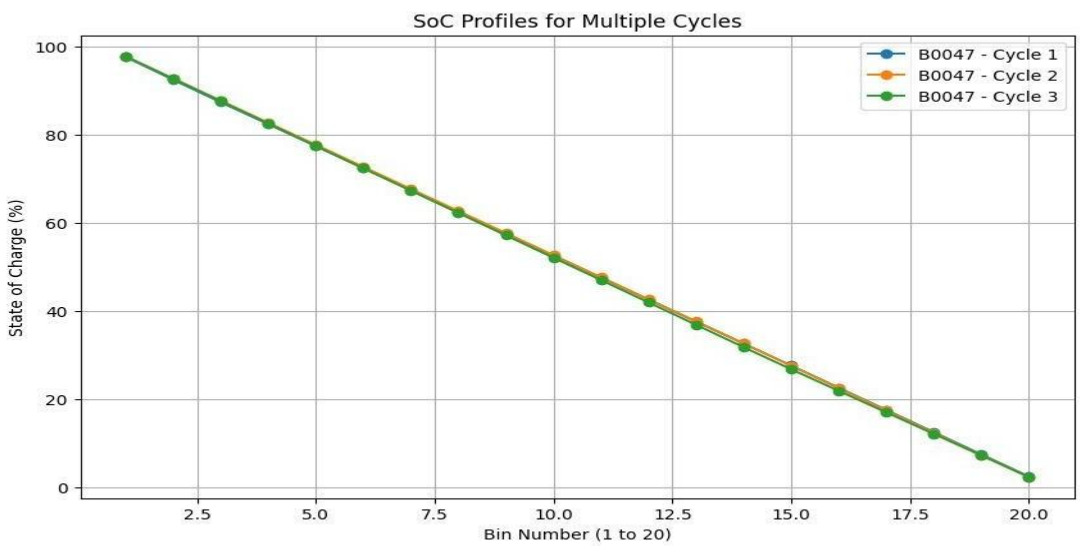

Fig. 18. SoC Profiles for Multiple Cycles

Throughout multiple cycles of discharge, the profiles of the State of Charge (SoC) fall in almost identical lines with one another across the entire range of State of Charge (SoC) points decreasing from about 98% (at bin 1) to roughly 2% (at bin 20). There does not appear to be much difference at any of the bin numbers between Cycle 1, Cycle 2, and Cycle 3; therefore, each cycle is demonstrating stable battery characteristics and there is little short term capacity loss. The repeatability you see when reviewing the curves in Fig. 18 demonstrates that there, together, is sound data, (from the previous experiments), which supports that the methodology used with averaging per bin is effective. Repeatability of results across cycles also gives a very strong foundation for improved accuracy in estimat ing SOC and SOH, which ultimately enhances the strength of AI model training for Electric Vehicle's (BMS).

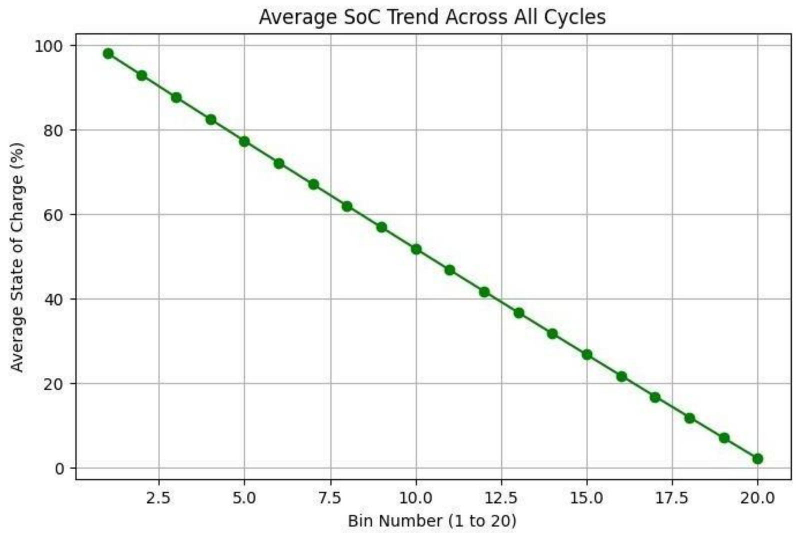

Fig. 19. Average SoC Trend across All Cycles

The overall average trend of the State of Charge (SoC) through all of the cycles shows an almost linear/consistent rate of decrease from approximately 98% SoC to ~2% SoC over twenty cycles, thus indicating a uniform rate of discharge across cycles. The continuous rate of decrease without any abrupt spikes at any point in time would indicate that the battery consistently performed in a similar manner with respect to charge being utilized from it across all cycles. The averaged over all cycles SoC graph (see Fig. 19.) captures all the overall characteristics associated with how it will discharge and minimizes variability between the cycles.

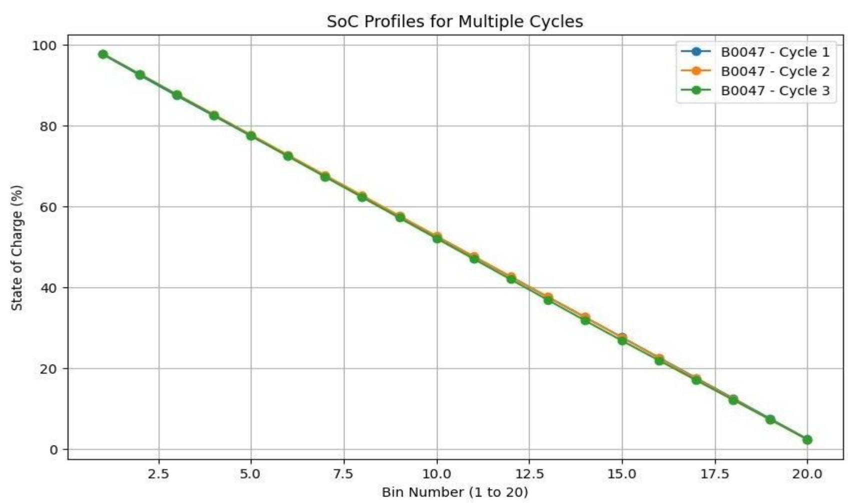

Fig. 20. SoC Profiles for Multiple Cycles

In terms of different discharge cycles, the patterns of state-of-charge (SoC) are very consistent and repeatable - they all have similar patterns (decrease from about 98% to almost 2%) overall across different bin numbers (i.e., bins 1 - 20). The close connections between all cycles (cycle 1, cycle 2 and cycle 3) indicate that there are low levels of variation between the different discharge cycles, which suggests that the batteries have consistent behaviour with negligible short-term degradation over time. The similar slopes of the three different profiles (see Fig. 20) show that the discharge characteristics are reliable, and that the process of binning of data is accurate. Therefore, this consistency helps to establish confidence in the ability to estimate S0C, therefore providing a solid base to support the use of artificial intelligence for modelling of both SoC and SOH within electric vehicle Battery Management Systems (BMS).

Table 5: Model Performance Comparison — SOC, SOH & Energy Loss Prediction:

Method	R^2	MAE (SOH)	RMSE (SOH)	ESP32 Deployable	Inference Latency
Coulomb Counting (Baseline*)	~.85	Higher	Higher	Yes (limited)	Real-time
Extended Kalman Filter (Baseline*)	0.89	Moderate	Moderate	Yes (complex)	Real-time
LSTM (This Work)	0.637	Highest	Highest	No (memory limit)	>200ms
XGBoost (This Work)	0.951	Low	Low	Partial	~50ms
Random Forest (This Work)	0.976	Lowest	Lowest	Yes (deployed)	<10ms

The table 2. provides a comparative evaluation of three AI models, including LSTM, Random Forest, and XGBoost, according to the R 2 values of predicting SOC, SOH, and energy loss in EV batteries. Random Forest has the largest R 2 of 0.976, indicating its better capacity to describe variation, and nonlinear patterns of battery degradation. XGBoost comes in close with a value of R2 of 0 .951 which means that it has great predictive reliability but with a little lower accuracy at extreme conditions. Conversely, LSTM demon strates R2 of 0.637, indicating low generalization, increased error in prediction and reduced sensitivity to complex behaviour of a battery.

Table 6: Live Hardware Validation Results from Prototype:

Test Condition	Measured Voltage (V)	SoC (%)	SoH (%)	Relay 1	Relay 2	Warning Triggered
Initial boot / full charge	12.6	~100	100	ON	ON	None
Mid discharge (observed)	9.87	39.4	100	ON	OFF	LOW VOLTAGE — Battery critical!
Lower discharge	9.5	30	100	ON	ON	None (at threshold)
Tier 1 trigger	9.8	<40	100	ON	ON	Low Bat! L1 OFF warning
Emergency shutdown test	≤8.0	<5	~100	OFF	OFF	EMERGENCY SHUTDOWN

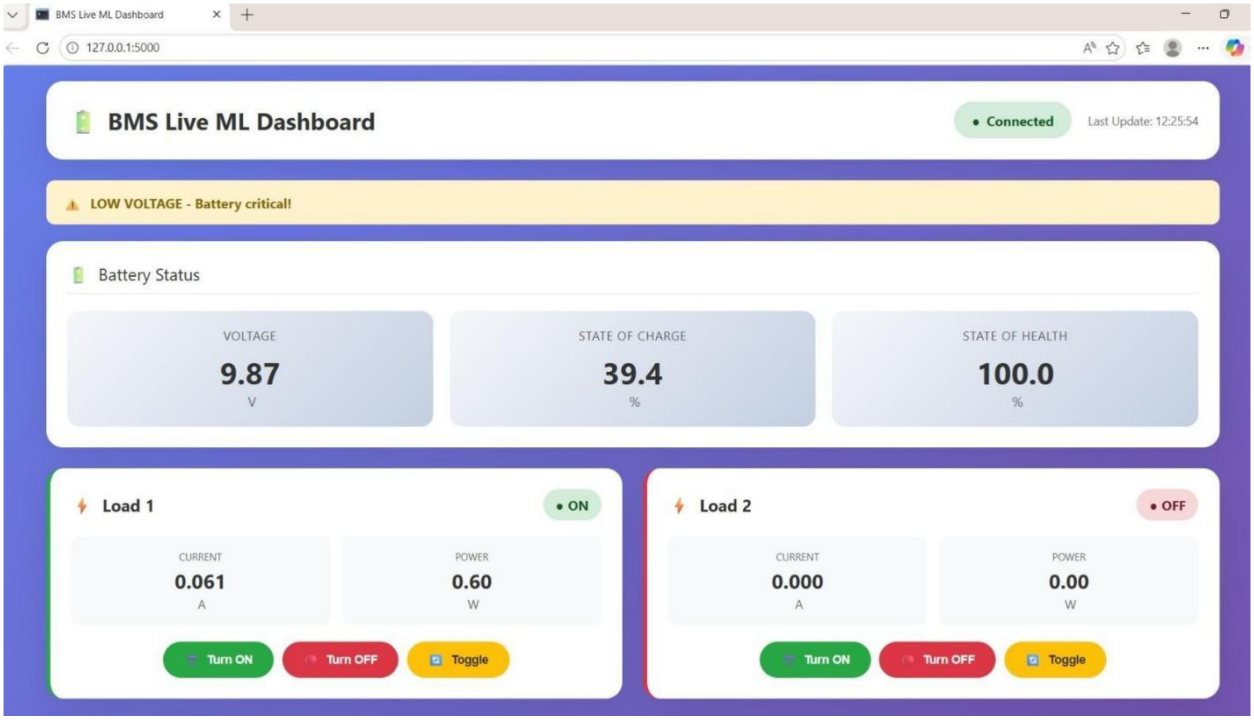

Fig. 21. Flask-SocketIO web dashboard

Figure 21 shows the Flask-SocketIO web dashboard running in 127.0.0.1:5000 in a live experimental test, which shows real-time telemetry broadcast by the ESP32 over MQTT broker. The battery status is indicated by the dashboard with a terminal voltage of 9.87V, and this is not equal to or above the 10.0V Tier 1 threshold specified by the ESP32 protection algorithm, prompting the amber text to change to LOW VOLTAGE - Battery critical! at the top of the interface. The Battery Status panel shows a concurrent report of SoC = 39.4% and SoH = 100.0% which is aligned with the early-cycle operation that is recorded in this test session. The Load 1 panel (status indicator ON, green border) measures a current draw of 0.061A and power usage of 0.60W, which is the on -board LED lamp through Relay 1. Load 2 (red border, status OFF) indicates zero current and power, which indicates that the ML classifier decision output properly isolated the secondary load at this current level. The time of update (12:25:54) is the real-time update time, which shows that the data between sensor acquisition and MQTT broker to browser rendering via WebSocket has a latency of less than 3 seconds, indicating that the system is appropriate in terms of operational BMS monitoring.

The Turn ON/ Turn OFF / Toggle relay control buttons that are visible in each load panel have a bidirectional control facility where remote relay override is possible regardless of the autonomous ML decisions.

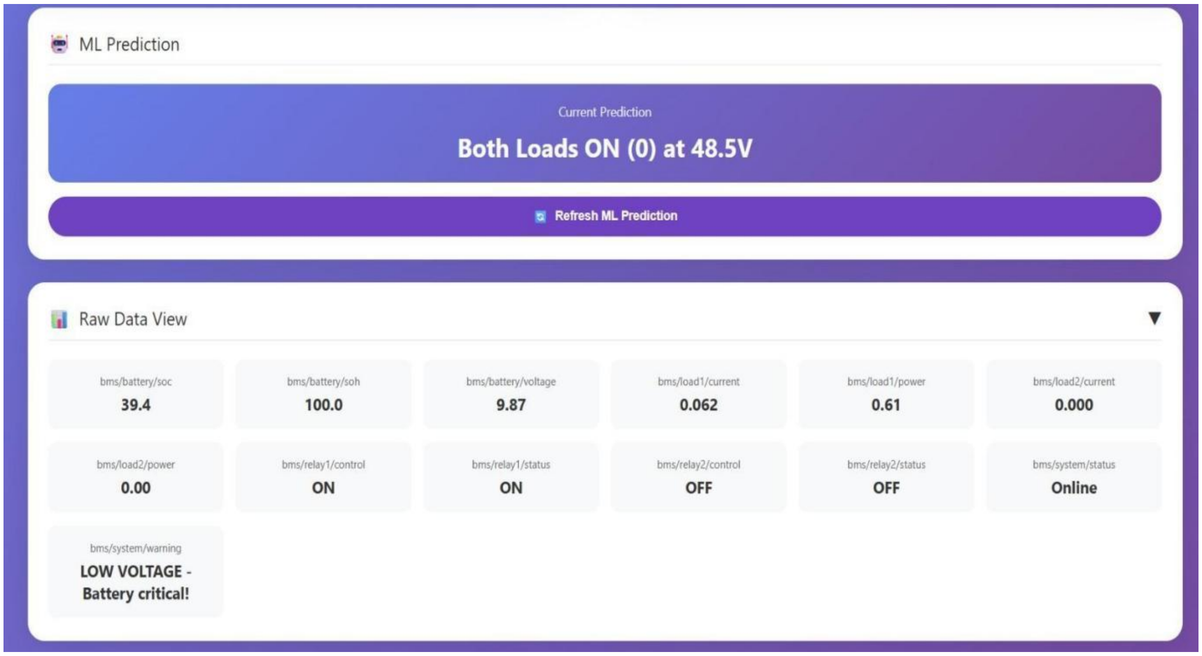

Fig. 22. ML Prediction panel and Raw Data View from the Flask dashboard

Figure 22 records the ML Prediction panel and the Raw Data View part of the Flask dashboard, offering full visibility of both the AI decision layer and MQTT data bus. The ML Prediction panel indicates: Both Loads ON (0) at 48.5V, which means that the RandomForestClassifier trained on the bms_dataset.xlsx file has predicted Decision Class 0, or the load configuration that maximizes the voltage input, the maximum load configuration, based on the voltage input feature. This 48.5V is the default voltage specified in the Flask server data dictionary on startup before the initial MQTT message is received, and subsequently when live MQTT data is received, the prediction is updated with the actual measured voltage. The Raw Data View panel will reveal all 13 active MQTT topics at once, and validate end-to-end data flow throughout the entire IoT pipeline: the ESP32 publishes bms/battery/voltage = 9.87, bms/battery/soc= 39.4, bms/battery/soh = 100.0, bms/load1/current = 0.062, bms/load1/power = 0.61, bms/load2/current = 0.000, bms/load2/power = 0.00, and bms/system/status = Online at 2 -second intervals, while bms/relay1/control = ON, bms/relay1/status = ON, bms/relay2/control = OFF, bms/relay2/status = OFF reflect the current relay state, and bms/system/warning = 'LOW VOLTAGE — Battery critical!' confirms the active protection alert. This full topic-level visibility not only authenticates the entire MQTT architecture characterized in Table [MQTT Topics Table] but it also verifies that the entire 13-channel communication architecture is in place throughout the entire system in live operation.

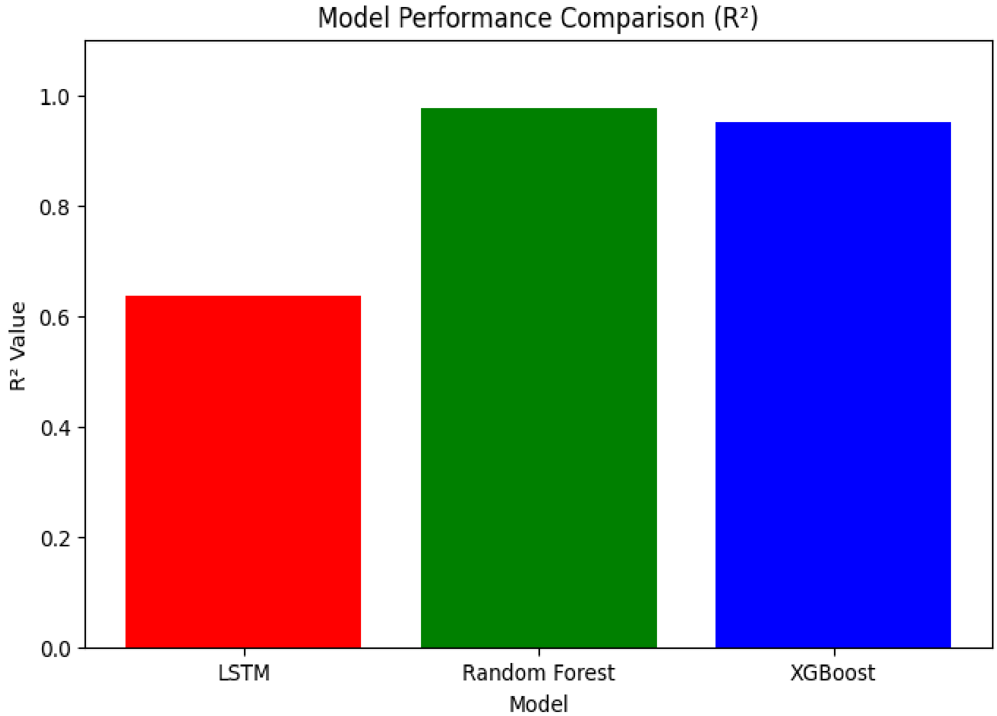

Fig. 23. Model Performance Comparison (R2)

Random Forest has the highest bar, and it is evident that it is a better predictor as compared to the other models. XGBoost has a high bar as well, justifying its efficiency in the modeling of battery related results with a strong accuracy. The LSTM bar is significantly shorter, which indicates that the model does not identify long-term dependencies and non-linear changes that exist in the battery data. On the whole, the graph highlights the superiority of ensemble learning methods in particular the Random Forest over deep sequential models in the accurate prediction of SOC, SOH, and the energy loss.

4.CONCLUSION

The overall analysis of the AI-based methods of SOC, SOH, and energy-loss estimations proves that Artificia l Intelligence can considerably improve the accuracy of Electric Vehicle Battery Management System (BMS), its strength, and flexibility. Through validated NASA lithium-ion battery datasets and comparison of three modelling methods Random Forest, XGBoost and LSTM, the study provides unequivocal results that ensemble learning methods are more effective in providing predictive power. Random Forest had the best accuracy $R^2 = 0.976$, the lowest MAE and RMSE, thus supporting its unparalleled ability to predict nonlinear battery degradation and reliably predict SoH and energy loss. XGBoost was also a strong model with $R^2 = 0.951$, which gives stable prediction s at the cost of a slight decreased sensitivity in extreme operating conditions. Comparatively, LSTM gave the worst performance with $R^2 = 0.637$, showing more error dispersion and inability to model long-term patterns of deterioration. The results of the feature-importance further indicated that the most significant predictors of energy loss were current (0.53 weight) and cycle count (0.30 weight), and that voltage and SOC played a minor role. Coherent SoC discharge profiles between cycles confirmed the qua lity of the data set and enhanced the modelling pipeline reliability. In addition to benchmarking at the dataset level, this paper is the first to show full hardware deployment: the trained Random Forest classifier is deployed to a Flask-MQTT server that communicates to an ESP32 microcontroller, allowing real-time AI-controlled relay control of a real 3S lithium-ion battery pack of ICR-18650. Live experimental measurements V=9.87V, SoC=39.4%, SoH=100%, Load 1 at 0.061A/0.60W Vindicated that AI -predicted battery states are highly similar to measured sensor values, the system is properly reacting to LOW VOLTAGE warnings, and staged load -

shedding is occurring autonomously. Combining the dual INA219 sensing architecture, the MQTT-based IoT communication over 13 topics, Flask-SocketIO web dashboard, and Tkinter desktop UI all together present the first experimentally validated, ML-controlled, and IoT-integrated BMS prototype reported in the literature on ESP32 hardware. Future directions will involve extending the validation to the CALCE battery dataset to cross -chemistry generalisation and physics-informed constraints to the model training pipeline.

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