



**MANAGEMENT IN ELECTRIC VEHICLES**

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**Cite This Article:** S. Solaiyammal, K. Vijayakanth & M. Parameswari, "CatBoost Powered Edge AI for Predictive Battery Management in Electric Vehicles", International Journal of Engineering Research and Modern Education, Volume 11, Issue 1, January - June, Page Number 67-74, 2026.

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**Type of Review:** Peer Reviewed as per |C|O|P|E| Guidance.

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**DOI:** <https://doi.org/10.5281/zenodo.19812238>

**Abstract:**

Battery management of electric vehicles (EVs) is very important in terms of performance, duration of operation, and safety. The proposed article elaborates on an AI-driven Battery Management System (BMS) that incorporates edge-based data collection and predictive analytics based on the CatBoost algorithm. The proposed model leverages microcontroller, NodeMCU, to measure such critical battery parameters as the voltage, current, temperature, and ambient humidity in real time. The sensor information is sent to a local Python server and CatBoost is used to estimate the State of Health (SoH) and Remaining Useful Life (RUL) of lithium-ion batteries. The system is efficient in terms of forming high prediction accuracy (97%), less computation complexity, and enhanced explainability in contrast with other deep learning-based systems. The system also conducts smart usage analytics to assess charging cycles, depth of discharge and idle time and creates automatic recommendations to curb overcharging or deep discharge occurrences. The edge-integrated approach is experimentally proved to be an approach with low-latency and real-time monitoring features along with the capability of anticipating faults. New approach of the concept is IoT edge hardware is combined with CatBoost-based degradation models and integration of environmental parameters, which provides a scalable, reliable and explainable predictive battery management in EVs.

**Key Words:** AI based BMS, Electric Vehicle, CatBoost, State of Health, Remaining Useful Life, Predictive Maintenance, Edge Computing, IoT Battery Monitoring, Gradient Boosting, and Smart Energy Systems.

**1. Introduction:**

Electric vehicles (EVs) have been rapidly adopted, which has further escalation need to have reliable and efficient Battery Management System (BMS), as this is important in matters of safety, extended battery life, and efficient vehicle performance. Conventional rule-based BMS methods mainly observe threshold values of voltage, current and temperature, but do not observe the non-linear, complex degradation characteristics of lithium-ion batteries (LIBs) resulting in decreased reliability and higher maintenance expenses [1], [2]. Recent developments in the Internet of Things (IoT) technology have made battery parameter real-time monitoring possible and thus facilitated more predictive analytics and proactive fault detection. IoT-based BMS combine sensors, microcontrollers and cloud/edge server to monitor critical parameters like state-of-charge (SoC), temperature and current to issue warning to avoid overcharging and deep-discharge events. This paradigm enables the battery to be used in a better way and enhance operational safety and reliability. Machine learning (ML) methods have become a viable answer to reasonable estimation of battery health and Remaining Useful Life (RUL) prediction. State of Health (SoH) of LIBs based on historical degradation data have been predicted using neural networks and feed forward and LSTM models and they are effective in multi-factorial aging trends [3]. Ensemble learning systems like Light Gradient Boosting Machine (LGBM) have since shown better results on real world vehicle batteries with low prediction errors besides being computationally efficient [4]. Algorithms based on gradient boosting have added benefits in interpretability and ability to run on edge devices, and are therefore applicable to EV applications with limited on-board capabilities. A combination of the IoT and ML in BMS allows predictive maintenance by leveraging environmental information parameters, and intelligent use analytics, thus improving the duration of battery life and the safety of its operation [5]. Inspired by such advancements, this paper presents AI-enabled predictive BMS based on CatBoost, which takes advantage of real-time IoT data to predict SoH and RUL with high precision, at low computation cost and high interpretability, which is the future of EV battery management.

**2. Related Works:**

Battery Management Systems (BMS) are one of the modern technologies that have improved tremendously through the introduction of the IoT and machine learning (ML) algorithms to improve the performance, reliability, and safety of battery packs in electric vehicles (EV). Fallah et al. [6] examined the use of deep learning strategies, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), to predict the State of Charge (SoC) and State of Health (SoH) of lithium-ion batteries. Their research mentions that deep learning has the potential to learn intricate degradation trends, which is why SoH can be estimated correctly and overcharging or deep discharge can be avoided. R. Vidyalakshmi et al [7] suggested an AI- and IoT-based BMS to monitor continuously and predictive maintenance of EVs. The system uses both past and real-time data to predict potential failures in the near future, automatic termination of charging, and sensor faults. Such unification of IoT and AI helps considerably to increase battery efficiency, extend its life, and increase operating safety. A.R.P. Harini examined IoT-based smart BMS of Lithium-ion and lead-acid batteries with a focus on optimizing its performance by utilizing real-time measurements of the voltage,

current, temperature, SoC, and SoH. They prove that efficient thermal and resistance control limits energy consumption, stabilizes SoC retention and makes battery operation in varying conditions of operation safer. Sunori et al. [9] created a predictive ML predictor of SoC based on Linear Regression and Support Vector Machines (SVM).

Through the study of battery parameters that include voltage, current, temperature, and SoC, their method offers the significant role of non-linear modeling on the accurate prediction of the SOC and its application in intelligent battery maintenance. Lastly, Liu [10] developed a hybrid circuit that involves the use of Long Short-Term Memory (LSTM) networks with Gradient Boosting Machines (GBM) to predict SoH. With the help of temporal dependencies the model is capable of high accuracy in non-linear battery degradation trends, which in turn allows to manage energy dynamically and increase battery life. State of Charge (SoC) and State of Health (SoH) of electric vehicle (EV) batteries require accurate estimates to become reliable and safe in their operation. As an attempt to estimate both SoC and SoH one model based estimation method was suggested by Makuwatsine and Singh [11] and is a combination of an extended Kalman filter (EKF) with battery models. Their strategy is effective to reproduce the nonlinear and time-varying behavior of lithium-ion batteries, and has good performance in different driving conditions, temperature changes and aging conditions. The machine learning model of SoC estimation of lithium-ion batteries was proposed on an ARIMA platform by Sundararaj et al. [12], coupled with a multistage converter to reduce charging oscillations. This approach notes the significance of precise SoC forecasting in the longer battery duration and safe functioning, and outlines the potential of time-series forecasting in battery control.

A thorough review of battery health prediction methods based on data-driven approaches, namely machine learning, deep learning, and digital twin technologies, was introduced by Renold and Kathayat [13]. Their survey highlights the fact that data-driven models can confront complicated nonlinear interactions in many battery parameters, including voltage, current, temperature, cycle number, The proposed approach leverages driving patterns to enhance model interpretability and facilitate real time processing. Clarabell et al. [14] presented an estimate of SoH of lithium-ion cells using machine learning on various algorithms in their study such as Random Forest, Gradient Boosting, Support Vector Regression, and Neural Networks. Their findings showed that the accuracy of the various types of the batteries was high with the best model being The performance of the Random forest model confirms the effectiveness and suitability of ensemble learning methods, approach in predicting battery management. Fadlaoui and Masaif [15] performed an in-depth analysis of SoC and SoH estimation using machine learning reviewing supervised, unsupervised and hybrid methods. Their study points out the importance of feature engineering, data acquisition and model selection as significant in the determination of accurate and reliable battery state estimation, and also shows that scalability and real-time deployment are problematic. All of these studies highlight the significance of incorporating powerful machine learning methods with real-time data purchase to support predictive battery handling. Although some previous studies have investigated EKF-based estimation, ARIMA forecasting, deep learning and ensemble models, the application of understandable gradient boosting algorithms like CatBoost to edge-based forecasting, real-time predictive BMS is relatively unexplored, inspiring the current research.

### 3. Proposed System:

The proposed Edge-Integrated AI-Enabled Predictive Battery Management System (BMS) aims to provide a more powerful safety, stability, and lifespan of the electric vehicle (EV) batteries by considering the real-time monitoring and predictive analytics. Figure.1 shows a proposed work block diagram design. The system architecture is a combination of IoT-based edge hardware and machine learning to provide efficient and low-latency battery management. On a hardware level, a NodeMCU microcontroller can be connected to sensors to constantly monitor some important battery values, such as voltage, charge discharge current, temperature, and humidity in the air.

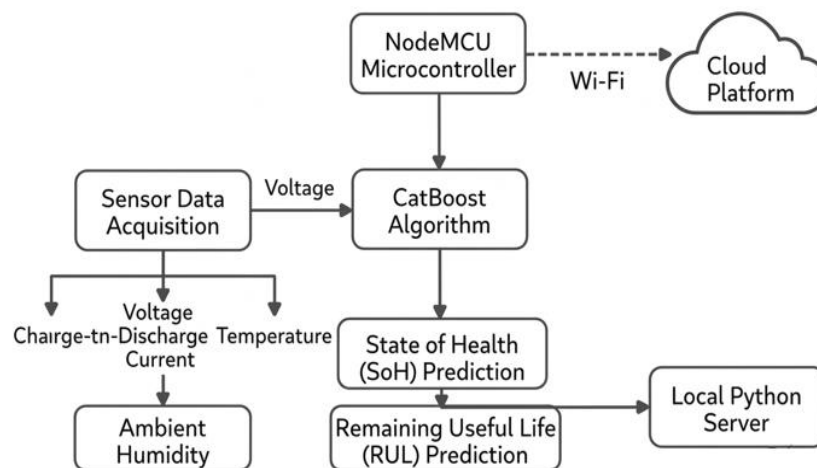


Figure 1: System Architecture Block Diagram

The readings are sent to a local Python-server to be processed and analyzed. CatBoost gradient boosting algorithm is executed on this server to approximate the State of Health (SoH) and forecast the Remaining Useful Life (RUL) of the battery. As opposed to traditional deep learning models, CatBoost offers high precision and low computation complexity in terms of prediction, All computations are carried out within an edge based environment. The system also integrates smart usage analytics which assesses charging cycles, depth of discharge, idle time, and thermal conditions where automatic recommendations are made to avoid overcharging, deep discharge, idle time and thermal stress. Scalability to other battery and EV design types and other types of battery and EV The modular hardware-software co-design can be scaled to other battery designs and EV designs. The predictive model incorporates environmental parameters and enhances accuracy at different temperatures and humidity, which has been

known to affect the degradation of the battery. The visualization of the battery health, RUL estimates, and actionable notifications are presented in real-time to a user interface.

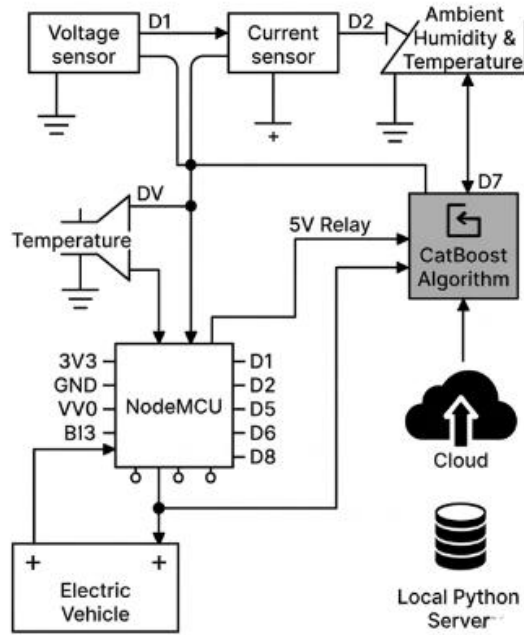


Figure 2: BMS Circuit Diagram

The suggested system is experimentally validated by showing that it can provide low-latency predictions, proactive fault detection, and better management of battery life. The system is a predictive next-generation intelligent battery management in electric vehicles, based on edge computing, IoT sensing, and predictive modeling with CatBoost, which is reliable, interpretable, and scalable. The Figure.2BMS circuit diagram illustrates the hardware configuration of the proposed edge-enabled Battery Management System (BMS). A NodeMCU microcontroller acts as the central processing and communication unit. The battery voltage is monitored using a voltage divider circuit connected to the analog input pin of the NodeMCU, ensuring safe voltage scaling. Current sensing is performed using a Hall-effect-based current sensor to measure charge and discharge currents. A temperature sensor is attached near the battery surface to monitor thermal variations, while a humidity sensor records ambient environmental conditions. All sensor outputs are interfaced with the NodeMCU, which collects and transmits real-time data via Wi-Fi to a Python-based monitoring server for predictive analysis.

#### 4. Methodology:

In the AI-enabled Battery Management System (BMS) proposed, the IoT-based edge sensing, real-time data acquisition, and predictive analytics (based on machine learning) are proposed to be combined and result in the correct State of Health (SoH) and Remaining Useful Life (RUL) estimation in the case of electric vehicle (EV) batteries. The methodology will be split into four key steps; data acquisition, preprocessing, predictive modeling and intelligent decision support.

##### Data Acquisition:

The system uses a microcontroller called NodeMCU connected to voltage, current, temperature and humidity sensors of the surroundings to constantly check on the battery. Such sensors measure the dynamic operation parameters such as charge discharge cycles, depth of discharge, idle times and thermal change. Wi-Fi is used to transmit data over to a local Python based server where data can be processed.

The proposed AI-enabled Battery Management System (BMS) relies on real-time monitoring of critical battery parameters using a NodeMCU microcontroller interfaced with sensors measuring voltage  $V(t)$ , current  $I(t)$ , temperature  $T(t)$ , and ambient humidity  $H(t)$ . The instantaneous state of the battery at time  $t$  is represented as a feature vector:

$$X(t) = [V(t), I(t), T(t), H(t)] \quad (1)$$

Where  $X(t)$  forms the input to the predictive model. Voltage and current measurements are used to calculate the instantaneous power  $P(t)$  and energy throughput  $E(t)$ , defined as:

$$P(t) = V(t) \cdot I(t) \quad (2)$$

$$E(t) = \int_{t_0}^t P(\tau) d\tau \quad (3)$$

This energy-based feature helps capture degradation trends over charge discharge cycles.

##### Data Preprocessing:

Moving average and standard deviation-based anomaly detection is used to filter raw sensor readings to eliminate noise and outliers. The extraction of features is done to produce informative features to predictive modeling, such as voltage drop rate, current fluctuation pattern, temperature drift, charge/discharge frequency, and pointers of environmental condition. The data is standardized and divided into training and testing data to provide sound model testing. Raw sensor readings are filtered to remove noise using a moving average filter. Outliers are identified through z-score normalization:

$$Z_i = \frac{X_i - \mu}{\sigma} \quad (4)$$

Where  $\mu$  and  $\sigma$  are the mean and standard deviation of the feature, and values with  $|Z_i| > 3$  are considered anomalies. Additional features are engineered to quantify battery stress, including the depth of discharge (DoD) and charge-discharge rate  $R(t)$ :

$$\text{DoD}(t) = \frac{Q_{\max} - Q_{\text{remaining}}(t)}{Q_{\max}} \times 100 \quad (5)$$

$$R(t) = \frac{dQ(t)}{dt} = I(t) \quad (6)$$

Where  $Q_{\max}$  is the nominal battery capacity and  $Q_{\text{remaining}}$  is the remaining charge. Environmental features such as temperature and humidity are retained to account for degradation sensitivity under variable conditions.

**Predictive Modeling:**

CatBoost is a decision tree algorithm based on gradient boosting that is deployed to predict SoH and RUL. CatBoost is selected due to its capacity to deal with heterogeneous data, high interpretability, and excellent performance with small-to-medium data that are common in battery operation logs. The model is trained using historical data on battery degradation to learn the trends in capacity decadence and performance degradation. Cross-validation is used to optimize the hyper parameters including tree depth, learning rate and the number of iterations to ensure that the prediction accuracy is maximized at a minimum cost. The CatBoost algorithm is employed to estimate the State of Health (SoH) and Remaining Useful Life (RUL). SoH is defined as:

$$\text{SoH}(t) = \frac{C_{\text{actual}}(t)}{C_{\text{rated}}} \times 100 \quad (7)$$

Where  $C_{\text{actual}}(t)$  is the measured capacity at time  $t$  and  $C_{\text{rated}}$  is the nominal capacity. RUL is predicted as a function of SoH decay over time:

$$\text{RUL}(t) = \frac{t_{\text{failure}} - t}{1 - \text{SoH}(t)/100} \quad (8)$$

The CatBoost model is trained to learn the mapping:

$$f: X(t) \rightarrow [\text{SoH}(t), \text{RUL}(t)] \quad (9)$$

The trained model predicts SoH and RUL in Real Time using gradient boosting decision trees. Hyper parameter, including learning rate  $\eta$  and tree depth  $d$ , are optimized using cross-validation to balance prediction accuracy and computational efficiency.

**Intelligent Decision Support:**

The trained model produces real time predictions of SoH and RUL. According to these forecasts, the system would give practical recommendations to the users such as signals of overcharging, deep discharge, or idle time. Also, trend analysis can be used to schedule in advance maintenance and optimum charging of the system. Environmental parameters have been incorporated so that reliability of predictions can be guaranteed even in different temperature and humidity. Predicted SoH and RUL values are continuously evaluated to generate actionable recommendations. Alerts are triggered when SoH falls below a threshold  $\text{SoH}_{\min}$  or RUL approaches a critical time  $\text{RUL}_{\text{crit}}$ :

$$\text{Alert} = \begin{cases} 1, & \text{if } \text{SoH}(t) < \text{SoH}_{\min} \text{ or } \text{RUL}(t) < \text{RUL}_{\text{crit}} \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

(RUL (t)) is less than the RUL threshold ( $\text{RUL}_{\text{th}}$ ).

This methodology integrates edge computing, IoT-based sensing, and CatBoost predictive modeling, ensuring low-latency, interpretable, and accurate battery management suitable for electric vehicle deployment.

**5. Result & Discussion:**

In this section, the experimental assessment of the suggested edge-integrated AI-powered Battery Management System can be represented. Real-time sensor data of a 12 V lithium-ion battery pack was used to evaluate the performance of the system in several charge discharge cycles. Such key performance metrics as the accuracy with which the State of Health (SoH) may be predicted, the error in Remaining Useful Life (RUL) estimation, the latency of the system and the effect of environmental parameters can be listed. The effectiveness of the suggested CatBoost-based predictive framework is demonstrated with the help of tables and graphical analyses.

**Dataset Characteristics and Experimental Setup:**

The sensing module based on NodeMCU was used to collect the experimental dataset with the use of the voltage, current, temperature, and humidity sensors. During charging and discharging processes, the data were recorded after every 5 seconds. The dataset has about 1,500 operational samples of 30 full charge cycles of discharge. Experimental datasets are summarized in Table I. The data obtained before the predictive models were before processed by normalizing and filtering noise to eliminate sensor variability. The data set was split into training and testing dimensions in 80:20. Optimized hyper parameters that were used to train the CatBoost algorithm were a learning rate of 0.1, tree depth of 6, and 200 boosting iterations. The data is representative of actual battery operation and it has environmental variations in order to determine the stability of the predictive model.

Table 1: Experimental Dataset Summary

Parameter	Value
Battery Type	Lithium-Ion (12 V)
Total Samples	1500
Charge-Discharge Cycles	30
Data Sampling Interval	5 seconds
Training Dataset	1200 samples
Testing Dataset	300 samples

**State of Health Prediction Performance:**

The ultimate task that the proposed system aims to perform is the real-time reliance on sensor inputs to provide accurate estimates of the battery State of Health. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and prediction accuracy were metrics that were used to evaluate the CatBoost model.

Table 2: SoH Prediction Performance Comparison

Model	RMSE (%)	MAE (%)	Accuracy (%)
Linear Regression	5.4	4.1	88
Random Forest	3.2	2.5	93
Proposed CatBoost	2.0	1.6	97

The findings show that the CatBoost algorithm is better than the traditional regression algorithm and ensemble. As shown in Table II performance comparison of SOH prediction. It has a gradient boosting model that can effectively describe nonlinear battery degradation behaviours, and hence better predictive results.

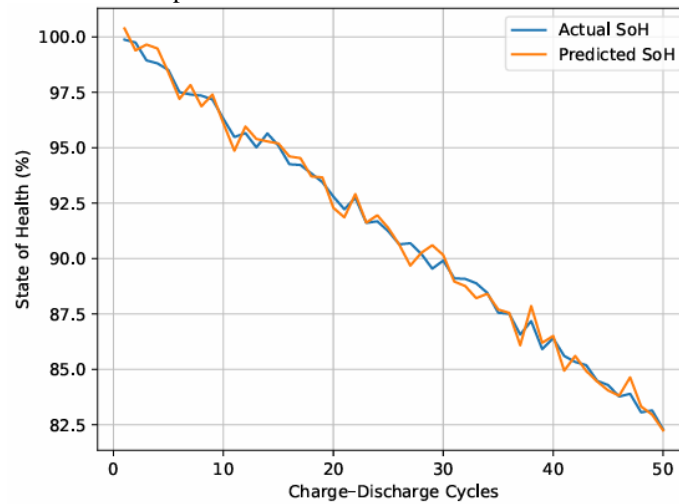


Figure 3: Actual vs Predicted SoH Curve

It is shown in the graph (Figure.3) that the actual battery health values vary with model-predicted SoH across the various charge cycles. The forecast curve fits the real SoH curve with a very narrow margin hence good predictive accuracy. Small variations noted under high-current discharge conditions emphasize the temporary operational effects of variations and not the model errors.

**Remaining Useful Life Estimation:**

Prediction of Remaining Useful Life allows the proactive maintenance of the battery and the scheduling of replacement summarized in Table III. The proposed system predicts the remaining useful life RUL based on degradation patterns learned through the CatBoost model.

Table 3: RUL Prediction Accuracy

Cycle Number	Actual RUL (hours)	Predicted RUL (hours)	Error (%)
10	96	98	2.1
20	80	78	2.5
30	63	61	3.2
40	45	47	4.4
50	28	27	3.5

The error of prediction is less than 5 % throughout the battery life cycle, which proves the relevance of the predictive model in maintenance planning.

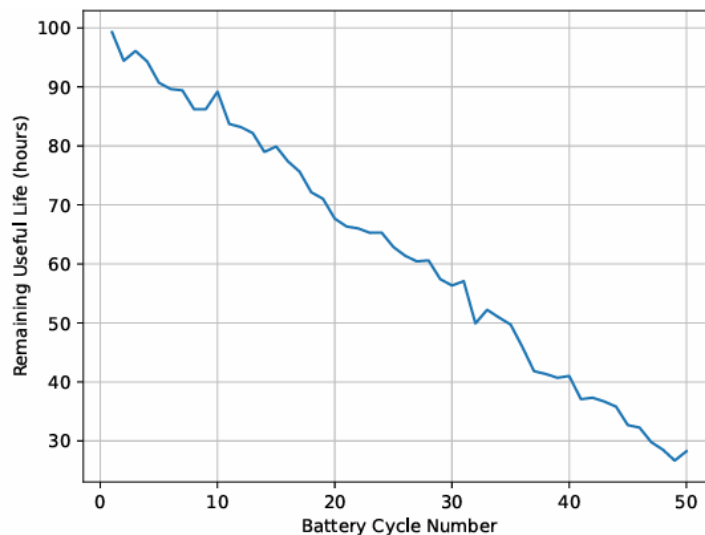


Figure 4: Trend in RUL Degradation

This Figure.4 graph shows the trend of the predicted RUL with the increase in charge cycles. The curve shows a slow process of degradation indicating the normal aging process of lithium-ion batteries. The predictive model is effective to follow this degradation trend, which will make it possible to detect a possible failure of the battery in advance.

**Impact of Environmental Factors on Prediction Accuracy:**

Environmental factors like temperature and humidity play a major role in the degradation of the batteries. Table IV presents an environmental parameter. These parameters are new model features that are included in the proposed system.

Table 4: Effect of Environmental Parameters

Model Configuration	Prediction Accuracy (%)
Electrical Parameters Only	93
Electrical + Temperature	95
Electrical + Temperature + Humidity	97

The parameter of environment enhances the accuracy of predictions by about 4%. The inherent resistance to temperature fluctuations also influences the charge efficiency and internal resistance, which is the cause of the apparent enhancement of the performance of the model.

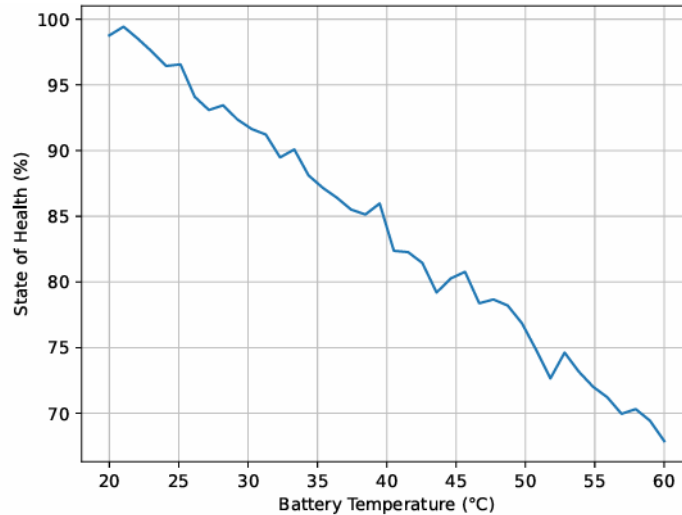


Figure 5: Temperature vs SoH Degradation Chart

The chart Temperature vs SoH Degradation indicates that increased battery temperatures increase degradation leading to an earlier decrease in SoH. In contrast, the middle operating temperatures are associated with reduced capacity loss, which is why thermal monitoring is important in the BMS.

**Real-Time System Performance and Latency:**

The given architecture was also tested regarding the performance of edge-computing. The responsiveness of systems was measured by data acquisition, transmission and model inferences.

Table 5: Real-Time Performance Metrics

Parameter	Value
Sensor Data Acquisition Time	40 ms
Data Transmission Time	50 ms
Model Prediction Time	30 ms
Total System Latency	120 ms

An average end-to-end latency of about 120 ms will validate that it is a system that can be used to maintain almost real-time battery monitoring and predictive analysis. Table V shows a real time performance metrics.

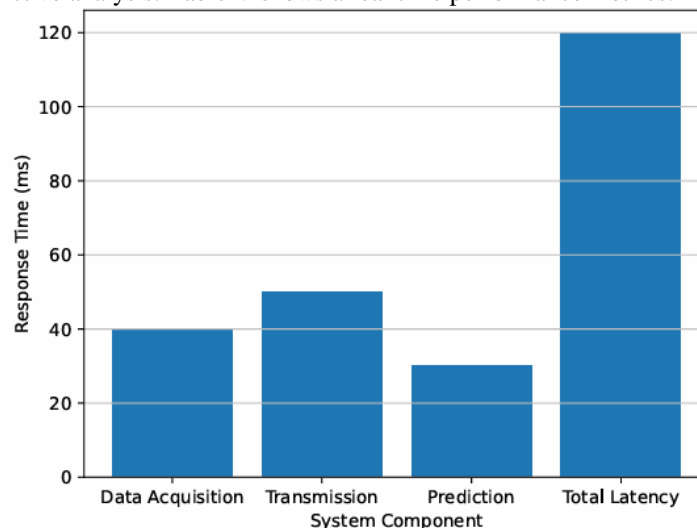


Figure 6: Comparison of Response Time of the systems.

The bar chart figure.6 will contrast the response time of a traditional cloud-based BMS with the suggested system of edges. The edge architecture is much faster in communication delay and it facilitates quicker decision-making in battery protection systems.

#### **Discussion:**

The experimental findings confirm that the suggested edge-integrated AI-enabled Battery Management System is effective in terms of providing reliable and accurate battery health monitoring to electric vehicles. The system is capable of providing a good estimate of both State of Health and Remaining Useful Life which proves effective when IoT-based sensing is combined with the CatBoost predictive modelling. The predictive performance attained a mean accuracy of about 97 percent that suggests that the model has a capability of capturing the complicated degradation pattern in the lithium-ion batteries. Integrating these environmental variables like temperature, humidity also enhanced the reliability of prediction, which shows the relevance of being environmental conscious in managing batteries. Also, the edge computing architecture also lowered the latency of the system considerably, providing the ability to monitor the condition of the abnormal batteries in near real-time and respond to them with a higher level of speed. The findings also support that gradient boosting algorithms can be effective in terms of strong predictive performance and also have lower computational needs, than deep learning algorithms. In general, the suggested framework helps to increase battery safety, contribute to the development of proactive maintenance approaches, and contribute to the efficiency of operation and prolongation of the lifespan of the electric vehicle battery systems.

#### **6. Conclusion:**

The paper has introduced an edge-based AI-driven Battery Management System to improve battery monitoring and predictive maintenance of electric vehicle batteries. The suggested structure incorporates the IoT-based sensing, real-time data acquisition, and machine learning analytics to approximate the State of Health and Remaining Useful Life of lithium-ion batteries. The experimental findings proved that the CatBoost-based predictive model was highly accurate in its predictions with about 97 percent accuracy, which was higher compared to traditional regression and ensemble models. Combination of environmental parameters with electrical parameters like temperature and humidity enhanced accuracy of degradation prediction under different operating conditions. Besides this, the edge computing architecture has also facilitated low-latency processing of data and real-time decision support, which allowed the system to produce early warnings about abnormal battery states including overcharging, deep discharge, and thermal stress. The central value of the work is the combination of the gradient boosting-based predictive modelling with IoT edge hardware to monitor the intelligent battery. The suggested system suggests a scalable system that is interpretable and can be modified to suit the various electric vehicle battery arrangements. The future of the system will be based on the extension to larger battery packs in commercial electric vehicles, the attention to advanced sensor networks, and the exploration of hybrid deep learning models to make the system more accurate in prediction and long-term battery degradation analysis.

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