IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 25 August 2024, accepted 5 September 2024, date of publication 16 September 2024,
date of current version 27 September 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3461802

RESEARCH ARTICLE

Remaining Useful Life Predictor for EV Batteries Using Machine Learning

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This work was supported by American University of Kuwait (AUK) Open Access Publishing Fund.

ABSTRACT The swift advancement of electric vehicle (EV) technology enhances the focus on sustainable energy storage and underscores the crucial significance of lithium-ion batteries. This research primarily presents the techniques of forecasting the Remaining Useful Life (RUL) of lithium-ion battery using advanced Machine Learning (ML) methods such as Random Forest (RF) and Support Vector Machine (SVM). This research centres around the thorough preprocessing of a detailed dataset received from the NASA Ames Prognostics Center of Excellence. The One-way ANOVA method is employed to find the optimum set of features. The exhaustive hyperparameter-tuning (HPT) was performed to boost the performance of the ML models. An important component of this study is its pragmatic methodology, which considered real-time variables such as temperature changes and usage cycles to analyses the effect on battery capacity (cap). The proposed system helped to understand the behaviors of battery deterioration trends more comprehensively. The effectiveness of the system is decided based on the R2 score and Mean Squared Error (MSE). The RF model has shown R2 score of 0.83 and MSE of 1.67. The result enhances lithium-ion battery safety and efficiency by establishing new predictive models. Thus, it provides a better battery management system for electric vehicles. As a result, it promotes the development of more sustainable and economical energy solutions.

INDEX TERMS Artificial intelligence (AI), electric vehicle batteries, machine learning (ML), remaining useful life (RUL), random forest (RF), support vector machine (SVM).

I. INTRODUCTION

This era of electrification progresses, characterised by the rapid expansion of renewable energy-based electrical vehicles. The significance of energy storage systems has increased considerably due to the increase in renewable energy-based systems. Li-ion batteries are considered superior to other energy storage technologies because they have a high energy density, robust power output, and low self-discharge rates [1], [2]. The increased relevance of this issue mandates more demands and obstacles for the progress of battery management technologies. A well-rounded battery management system (BMS) contains functions such as data gathering, status analysis and forecasting, control over charging and discharging, safety mechanisms, thermal management, balancing power, and communication systems [3]. The efficiency of a BMS is assessed by its accuracy in state estimate. A BMS that operates exceptionally ensures the energy storage system's stable functioning and prolongs battery life [4].

An ideal BMS should have multitasking skills and combine a real-time operating system for constant monitoring and rapid modifications.

Despite their advantages, Lithium-ion batteries have constraints, particularly their lifespan and cost, which prevent their larger deployment [5]. Battery performance deteriorates

The associate editor coordinating the review of this manuscript and approving it for publication was N. Prabaharan.

over time due to calendar ageing and cycle ageing, leading to numerous degradation events [6], [7]. Ageing not only raises operational costs but also reduces the lifespan of equipment and impairs safety [8], [9], [10]. A battery is generally deemed to have reached its end-of-life when its capacity decreases to 80% of its initial value [11]. The Remaining Useful Lifetime (RUL) is the predicted operational length from the current moment until the battery hits its end-of-life [12], [13], [14].

The composition of the battery and the chemical changes that occur within it throughout charge-discharge cycles determine its longevity. This ageing process is intricate and non-linear, which is further affected by parameters including temperature, charge/discharge rates, and the surrounding environment [15], [16], [17], [18]. Accurate prediction of RUL in complex situations is a major task. In industrial environments, correct RUL predictions may minimise investment costs and enhance profitability [19], [20]. It also helps in energy storage systems, boosting safety, stability and extending battery life [21], [22].

RUL has three prediction strategies: model base, data-driven, and hybrid methods [23], [24]. In the model base approach, the mathematical description of the internal battery physical and electrochemical reaction formulated for generate predictive models to know the current status of the battery [25], [26], [27]. The formulation of these models is a complex method and faces the problem of computational intensity because parameterizing electrochemical models follows the battery disassembly method, which is very challenging in practical application. However, it proves excellent accuracy once the model is prepared [28], [29]. At the same time, data-driven methods are formulated based on historical data. Therefore, these data-driven methods are more practical than the model-based approach due to the complicated nature of the Li-battery [30], [31], [32].

The prediction of Remaining Useful Battery (RUL) is very important for optimizing both performance and safety of the electrical vehicles. Therefore, this study predicts the remaining useful of electrical vehicle batteries more accurately by modelling historical data using supervised learning such as Random Forest (RF) and Support Vector Machine (SVM). The historical battery data is taken from NASA Ames Prognostics Center of Excellence (PCoE). The accuracy of the models is enhanced by techniques like feature selection. Various methods of feature selection, like one-way ANOVA and hyperparameter tuning, are applied in the research. The effective models are decided based on the value R2 and MSE of the models. The novelty of the study is getting the real-time data of battery capacity decline and temperature fluctuations as a result of the study. It also provides the association between the number of battery consumption cycles and the battery decline capacity percentage. This investigation was conducted utilizing Google Colab and a 12GB NVIDIA Tesla K80 GPU to support hardware acceleration. The dataset is split into training and testing groups for pre-processing and extracting essential features. The predictive models are finalised based on a comparative study of the prior research.

Zhu et al. [33] proposed an improved hybrid neural network, combining a bi-directional Long Short-Term Memory (Bi-LSTM). It provides a new method for forecasting Li-ion battery health using deep learning. The methods help in monitoring the complete health of the battery and its lifecycle from charging to discharging. Yang et al. [34] applied HPCC test to extract the battery related features. After that, the extracted features are given to the Back propagation neural network (BPNN) to predict the state of health of the batteries. Mitra et al. [35] used different machine-learning models to predict the battery life of Lithium batteries. The support vector Regressor (SVR) has shown the lowest error rate among all algorithms. Chun et al. [36] enhanced the reliability of the Li-ion battery by monitoring the health of the battery and capacity prediction by applying a Generalized Regression Neural Network (GRNN). The usability of the battery is further improved by forecasting its Remaining Useful Lifetime. Wu et al. [37] used the particle swarm optimizer with Random forest (PSO-RF) to predict the battery life. The feature optimization was not performed in this case. Ren et al. [38] merged an autoencoder with a deep neural network (DNN), adopting a 21-dimensional feature extraction technique using the autoencoder to represent battery health decline. The DNN model, trained on a real-world dataset from NASA, demonstrated excellent in multi-battery remaining cycle life estimation. A few drawbacks of the above literature are discussed in the following table-1.

TABLE 1. Literature survey.

Ref. No.	Method	Drawback
33	Bi-LSTM	Slow training, Resource expensive
34	BPNN	Suffers with overfitting
35	SVR	Absence of model tuning, inefficient feature selection
36	GRNN	Prone to overfitting, difficult to tune
37	PSO-RF	Absence of feature selection
38	DNN	Needs a large amount of data and slow convergence due to deep structure

II. PROPOSED SYSTEM

This research provides an intricate model aimed at forecasting the Remaining Useful Life (RUL) of electric vehicle (EV) batteries. The methodology, as represented in the workflow diagram, begins with painstaking data pre-processing, involving the imputation of missing values from a comprehensive dataset acquired from the NASA Ames Prognostics Centre of Excellence. Afterwards, the Feature selection and training

of machine learning models such as Random Forest and Support Vector Regressor was performed. The performance enhancement of the models was achieved by adjusting the Hyperparameter as shown in figure-1.

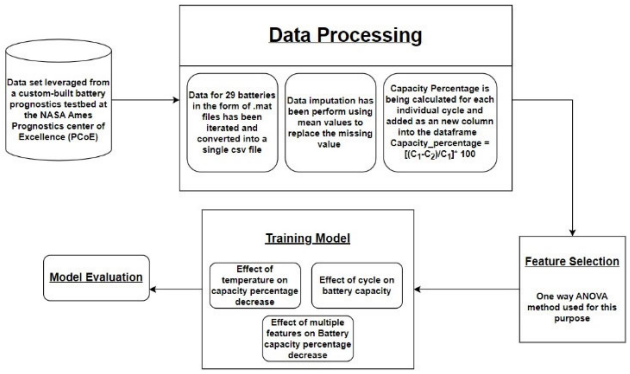

FIGURE 1. Methodology flowchart.

A. COLLECTION AND STRUCTURE

The dataset used in this work is acquired from a custom-built battery prognostics laboratory at the NASA Ames Prognostics Center of Excellence (PCoE). The data set is structured in cycles for 29 batteries in.mat file format, each having charge, discharge, and impedance operations. The data comprises multiple parameters, such as voltage, current, temperature, and impedance, acquired during different battery operations, as shown in Table 2.

TABLE 2. Battery data structure overview.

Data Type	Description
Cycle	Array of structures at the top level that Includes impedance, charge, and Discharge processes.
Operation type	impedance, charge, or discharge
Ambient temperature	Ambient temp (degree C)
Time	The beginning and ending timestamps of The cycle, as a MATLAB date vector
Data	Structure of data offering measures
Volts measured	Battery Terminal voltage (in volts)
Amps measured	Battery Output current (Amps)
Temp measured	Battery Temperature in Celsius
Amps charge	Measured current at the charger (in amps)
Volts charge	Measured voltage at the charger (Volts)
Time	Cycle time in second
Capacity	1 Battery discharge capacity in Ahr up to 2.7 V
Sense amps	Amps of current in the sense branch
Battery amps	Amps flowing through the battery's terminals
Current ratio	Combined current ratio
Battery impedance	Battery impedance in Ohms
Rectified impedance	The battery's impedance has adjusted and flattened in Ohms
Re	Electrolyte resistance in Ohms
Rct	Charge transfer resistance in Ohms

B. DATA PREPROCESSING

The originally iterated through each.mat file, representing individual battery cycles, to extract pertinent data. Then, this data was methodically formatted into a CSV file, boosting ease of handling and analysis. The missing values in the important features, including voltage, current, and temperature, were imputed with the mean value, for assuring the dataset completeness. The main objective of this investigation is to determine the capacity percentage of age (%age) for each cycle, using the formula in Equation (1):

$$\%\text{age} = ((C_1 - C_2)/C_1)^*100 \quad (1)$$

where C_1 is the maximum available capacity of the current cycle, and C2 is the maximum available capacity of the next cycle. This computation is essential for understanding the degradation patterns in EV battery life over multiple cycles.

Correlation Matrix Insights: The correlation matrix gives substantial insights into the relationship between various features and battery health. Temperature change and discharge indicate a considerable association with battery capacity, affirming the decision to do regression tasks on these variables, as shown in Figure 2.

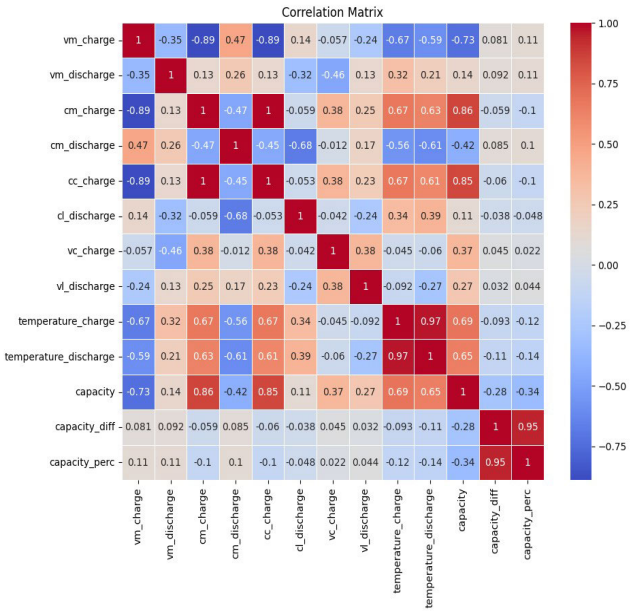

FIGURE 2. Correlation matrix.

C. FEATURE SELECTION

Selecting the most important features is essential for constructing precise predictive models. The study applies the One-Way Analysis of Variance (ANOVA) method as a credible statistical method to find features that have a substantial impact on battery degradation. In this process, the important features of battery life deterioration are selected carefully for analysis. It minimised the complexity of the model and enhanced the overall accuracy of prediction using the

ANOVA (Analysis of variation) method. The process is based on comparing the variation within groups to the variance between groups [39] based on F-statistic calculation using Equation (2):

$$F = (\sigma^2_{Btn\ grps})/(\sigma^2_{Within\ grps}) \tag{2}$$

where σ^2 represents the variance. The importance of the feature is decided by the F-value, as shown in Figure 3. The more important feature has a higher F-value. The impact of these features is more on the dependent variable.

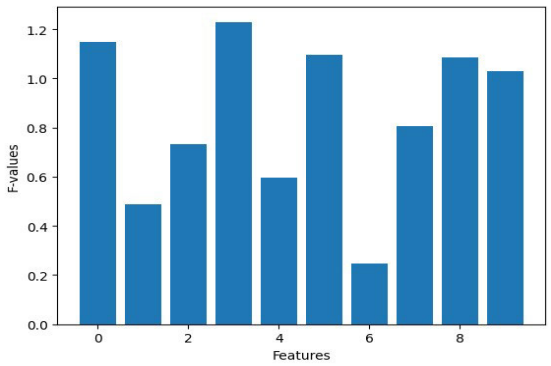

FIGURE 3. F-value using ANOVA.

D. TRAIN TEST SPLIT

The datasets are split into two parts for analysis using machine learning. 70% of datasets are allocated for training the model, and 30% of datasets are allocated for testing the model finalised based on accuracy during the training.

E. MACHINE LEARNING MODELS

There are many machine learning techniques that are used for data analysis. The model is decided on the basis of the type of dataset. RF and SVM are more suitable models for battery Remaining Useful Battery robust prediction. These models can handle high-dimensional data and capture complex relationships. Hyperparameter tuning is used to improve the model's performance.

1) RANDOM FOREST

It is a composite learning method utilized for regression or classification tasks. It creates a group of decision trees T during training. While making the prediction, it finds the mean regression outcome made by each decision tree. While creating the decision trees, a random subset with f-number of features is considered out of total features F. Due to this, diversity is added when constructing different decision trees. Different subsets of the original dataset are created with replacements for training each decision tree of the same size as the original dataset. Few records get repeated in each subset, whereas few are completely unique. In every node, branching occurs only if the number of samples contained by each node is more than the threshold value set for the minimum sample count hyperparameter. Setting a very high value for this hyperparameter mostly results in underfitting, and lower leads to overfitting of the decision tree. The aim of branch decision at any node in a decision tree is mainly to reduce the mean squared error e in the target feature, as shown in equation 3.

$$\mathrm{e} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \tag{3}$$

where y_i is the actual value, $\hat{y}$ is the predicted value, and N is the number of samples in the node.

During the tree creation, it generally goes to any level of depth without pruning, often leading the model towards overfitting. The decision tree aggregation will start after all the decision trees are constructed. During this phase, the average of prediction results produced by all trees is calculated as shown in equation 4.

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T}\hat{y}_t \tag{4}$$

where $\hat{y}_t$ the prediction of the t-th tree, and T is the total number of trees.

Algorithm for Random Forest-

Given a training Instance $D = \{(A_i, B_i)\}_{i=1}^{n}$, where A_i are the input features and B_i is the target value:

1. Training Phase:

➢ For each tree t in the forest (total T trees):

- Draw a bootstrap sample D_t from D.
- Grow a decision tree T_t on D_t by:
  - ❖ At each node, select a random subset of features.
  - ❖ Split the node using the feature that minimizes the MSE.
  - ❖ Continue splitting until stopping criteria are met (e.g., maximum depth or minimum samples per leaf).

1) PREDICTION PHASE:

➢ For a new input x, each tree T_t provides a prediction $\hat{y}_t(x)$.

➢ The final prediction $\hat{y}_t(x)$ is the average of all individual tree predictions.

a: RF OPTIMIZATION

The different hyperparameters of Random Forest are tuned for optimum performance. The 'random state' parameter is a numerical value that dictates the specific random arrangement used to divide the training and test data. In one instance, the chosen values by GridSearchCV for these parameters were: 'max depth' as [None, 10, 20, 30, 40, 50], 'n estimators' as [50, 100, 150, 200, 250, 300, 350, 400, 500], and 'min samples split' as [2], [5], [10], [15], [20] among which the best parameters were {'max depth': 30, 'min samples split': 2, 'n estimators': 400} [40].

2) SUPPORT VECTOR MACHINE

It is a type of machine learning algorithm used for classification as well as for regression. It performs the regression by

drawing a bestfit line and 2-marginal planes in each side of the best-fit line having an equal distance from the bestfit line, as shown in equation 5.

$$\mathrm{F(x)} = w^T * x \pm \epsilon \tag{5}$$

where w = slope of the bestfit line, x = input vector, ϵ = distance between bestfit line and marginal plane. Out of multiple possible marginal planes around the bestfit line the model selects a specific set of 2 lines having maximum distance between them. These lines can be created by drawing a line passing through the points closer to the bestfit line in both sides. The loss function can be minimized by minimizing the value of slope 'w' intercept 'b' and regulating the hyperparameters. The different hyperparameters of the support vector regressor are the number of points adjusted outside the marginal plane and the total distance of those points from the marginal plane. The different kernel functions are used for transforming the non-linear relationship between input features and target into a linear one. The detailed steps of SVR are depicted in the following algorithm [23].

Algorithm

Step 1: Define the Dataset

Suppose a dataset with n samples $\{(x_i, y_i)\}_{i=1}^{n}$

Where x_i is the independent feature vector, y_i is the continuous target variable. To find a function f(x) that can predict the value of y_i with lesser error.

Step-2: Create a bestfit line with following equation. $\boldsymbol{y = w^T * x + b}$ Where w = slope of the bestfit line, x = input vector, b = y-intercept, Let us assume b = 0 for simplicity

Step-3: Create equal distance marginal plane in both directions of bestfit line. $\boldsymbol{w^T * x \pm \epsilon}$

Step-4: Find the best set of marginal planes around the best fit line by maximizing the distance between them.

$$\max_{w,b} \frac{2}{||w||}$$

where $||w||$ is the magnitude of the slope of the line

Defining constraint for the function

$$y = \begin{cases} +1 & w^T * x + b \geq +1 \\ -1 & w^T * x + b \leq -1 \end{cases}$$

Step-5: Calculate the cost function by minimizing *w, b*

$$\min_{w,b} \frac{||w||}{2}$$

Step-6: Regulate the cost function by introducing the hyperparameters. (Linear problem)

$$\min_{w,b} \frac{||w||}{2} + c * \sum_{i=1}^{n} \varepsilon_i$$

where

c = Number of points adjusted outside marginal plane

ε_i is the sum total of all points lying outside marginal plane

Constraint = $|y_i - w_i * x| \leq \epsilon + \varepsilon_i$

Where

ϵ = *Distance between Bestfit line and marginal plane*

ε_i = *Distance between the point and marginal plane*

Step-7: Find the optimal value for Lagrange multipliers α_i and α_i^* (in the non-linear problem).

Step-8: Perform the final output prediction.

- Linear Problem: $f(x) = w^T * x + b$
- Non-Linear Problem: $f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) * K(x_i, x) + b$

Where K = Kernel function

The Kernel in SVR, comparable to SVM, is a measure of similarity, dictating the shape of the hyperplane in the higher-dimensional space. Common choices for the Kernel HP include linear and RBF (radial basis function). In the context of SVR, these Kernels help in transferring the data points into a higher dimension where a linear fit is possible. The RBF Kernel, for instance, is popular because of its effectiveness in handling non-linear correlations, offering a versatile method to accommodate a wide range of data patterns [41].

$$k(x_1, x_2) = \exp\left[-\left(\|x_1 - x_2\|^2\right) \Big/ 2\sigma^2\right] \tag{6}$$

where σ denotes variance, and $\|x_1 - x_2\|$ is the Euclidean distance between two points, x_1 and x_2 in equation (6).

a: SVR OPTIMIZATION

Here, the two important hyperparameters such as 'C': [6], [7], [8], [9], [10], [11], [12] and 'Kernel HP': ['linear','rbf'] are tuned to achieve the best performance of the model. 'C' tells about the count of points outside the marginal point. The job of Kernel functions is to transform the points with lower dimension space to higher. Using the GridSearchCV method, the best value for 'C' is found as '10', and the Kernel function is selected as rbf.

III. RESULTS

A. PREDICTION OF CAPACITY PERCENTAGE DECREASE DUE TO TEMPERATURE OF THE BATTERY

The Random Forest Regressor model is applied to predict the percentage decrease in battery capacity due to temperature change and discharge. The R2 score [42] obtained is 0.83, indicating a strong correlation between the predicted value of the dataset and actual values. The Mean Squared Error (MSE) [43] is 1.67, which signifies the value of the model accuracy in capturing the capacity decrease as shown in figure-4.

B. PREDICTION OF CAPACITY PERCENTAGE DECREASE DUE TO THE NUMBER OF CYCLES

Regression tasks employing the Support Vector Regressor are performed to predict the battery's capacity based on the number of cycles. The R2 scores fall within the range of 0.90 to 0.99, showcasing the model's effectiveness in capturing the

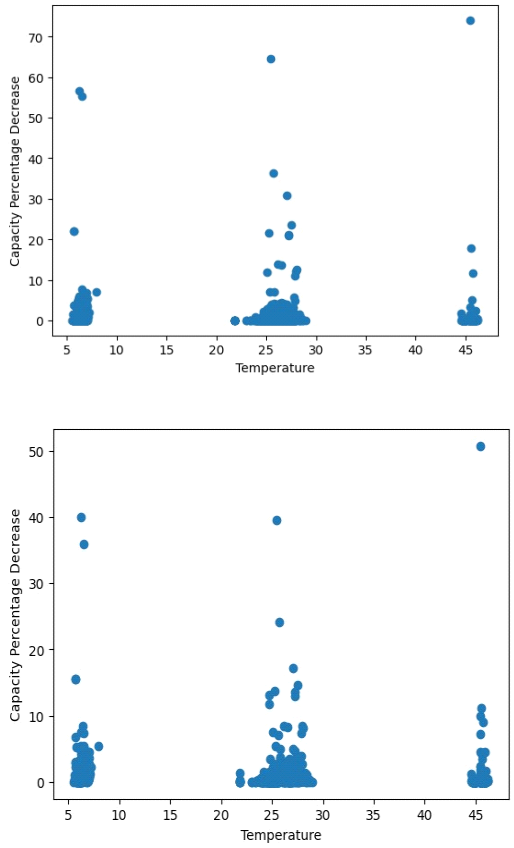

FIGURE 4. Capacity percentage vs. temperature (Actual - Predicted).

relationship between number of cycle and the battery's capacity as shown in figure 5, 6, 7, 8.

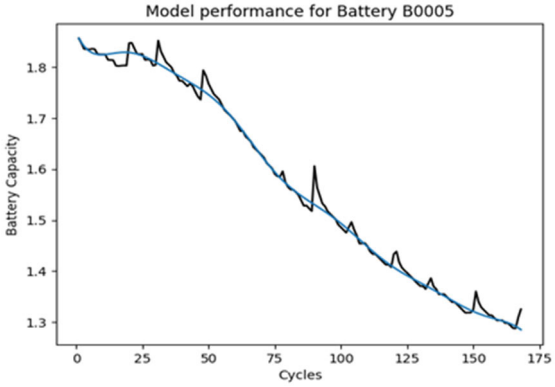

FIGURE 5. Battery-Cap vs. cycles for battery B0005.

C. PREDICTION OF CAPACITY PERCENTAGE DECREASE WITH MULTIPLE FEATURES

The Random Forest Regressor predicts battery capacity percentage decrease, considering multiple features such as voltage, current, and temperature. In total, seven such features are used. The R2 score is 0.73, and the Mean Squared Error is 1.9. This analysis provides insights into the combined impact of various factors on battery health.

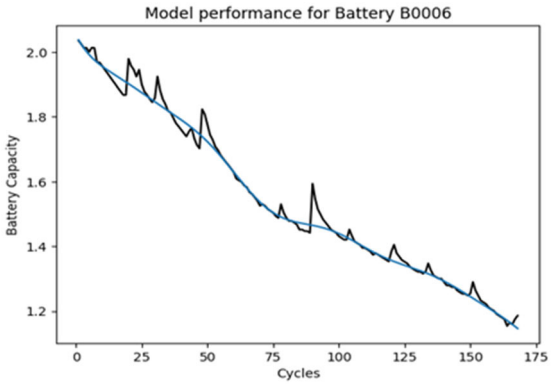

FIGURE 6. Battery-Cap vs. cycles for battery B0006.

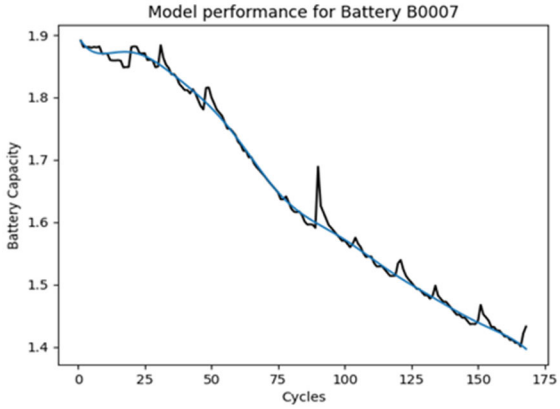

FIGURE 7. Battery-Cap vs. cycles for battery B0007.

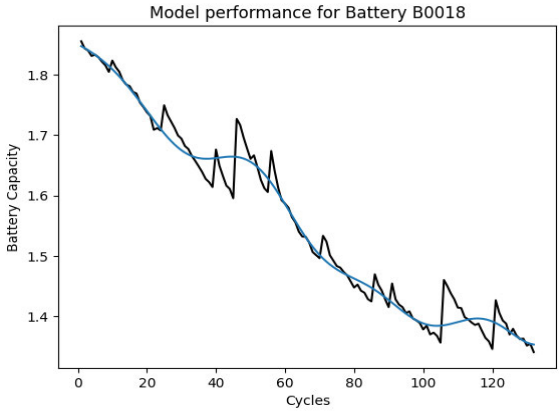

FIGURE 8. Battery-Cap vs. cycles for battery B0018.

IV. COMPARATIVE ANALYSIS

After investigating the different literature, a detailed comparative analysis is discussed in this section. Table 3 shows the prediction error of lithium-ion battery life using different AI-based methods. The proposed approach, utilising ML techniques like RF and SVM, outperforms others with an impressive R2 score of 0.83 and a Mean Squared Error (MSE) of 1.67. This higher accuracy stems from the focused

feature selection using one-way ANOVA, which narrows to seven crucial features, that is lesser than other studies. Other studies have either used extensive feature sets or needed more robust feature selection that is potentially leading towards overfitting. The proposed feature selection method and GridSearchCV based Hyperparameter tuning contribute to the model's precision, avoids overfitting and enhancing accuracy through optimal Hyperparameter value selection. Most of the studies employed deep learning techniques like Bi-LSTM [33], BPNN [34], GRNN [36], and DNN [38] for Li-ion battery health and RUL estimation. These methods are effective, but they are computationally intensive, leading to slower algorithm speeds. The reason behind the higher error percentage, shown by the DL models, is due to the use of less important features. Utilizing suboptimal features often leads to a decline in performance. Apart from this, most of the time, deep learning models suffer from the issue of vanishing gradient problems when the sample count is less. In SVR [35], feature selection was performed using the F-test, which is not always as efficient as an ANOVA test. The F-test provides a limited view by only comparing two groups simultaneously. ANOVA, on the other hand, evaluates the overall variance between multiple groups, giving a more comprehensive understanding of the relationships among the groups. In RF [37], the model hyperparameters are tuned using a particle swarm optimizer (PSO). The PSO method is not efficient enough as compared to GridSearchCV when the parameter space is not too large. The GridSearchCV method is most preferable when the numbers of Hyperparameters are not so high. Even though the PSO is faster many times, it does not guarantee the optimal value while searching for the global minima. The feature selection was also not conducted using this method. Hence, the model has shown a higher error percentage than the proposed model.

TABLE 3. Comparative analysis.

Ref No.	Method	Error
33	Bi- LSTM	2%
34	BPNN	5%
35	SVR	10.9%
36	GRNN	4.3%
37	PSO-RF	3%
38	Deep Neural Network (DNN)	6.66%
Proposed System (Tuned RF)		**1.67%**

V. CONCLUSION

This study indicates a substantial leap in estimating the RUL of Li-ion batteries in EVs, applying ML models like RF and SVM. The methodology comprised rigorous data preprocessing, where specific parameters affecting battery life were meticulously separated. Using One-way ANOVA, the research revealed seven key factors out of 10 significantly influencing the battery's RUL. The RF model earned an exceptional R2 score of 0.83 and an MSE of 1.67, indicating its accuracy in predicting capacity decline due to temperature fluctuations. These discoveries are pivotal for enhancing battery management systems in electric vehicles and offer a framework for future study in predictive modelling. The research continues by emphasizing the potential of expanding this strategy to embrace more diverse data sets and exploring the integration of deep learning techniques to refine forecast accuracy further. The work can be enhanced by including different sensors and Internet of Things (IoT) based devices for collecting real-time data on electrical vehicle batteries. The RUL of different EVs can be improved to a greater accuracy by applying hybrid machine learning-based analytics on the real-time data collected using sensors.

COMPLIANCE WITH ETHICAL STANDARDS

CONFLICT OF INTEREST

The authors declare that they do not have any conflict of interests that influence the work reported in this paper.

DATA AVAILABILITY

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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