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RESEARCH ARTICLE OPEN ACCESS

PREDICTING REMAINING USEFUL LIFE OF LITHIUM-ION BATTERIES FOR ELECTRIC VEHICLES USING MACHINE LEARNING REGRESSION MODELS

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ABSTRACT

Accurate prediction of a lithium-ion battery's remaining useful life (RUL) is essential for effectively managing and maintaining electric vehicles (EVs). By anticipating battery health and potential failures, we can optimize performance, enhance safety, and prevent costly breakdowns. Based on a supervised machine-learning regression approach, this work presents four different regression models like Gradient Boosting Regressor, K-Nearest Neighbor Regressor, Bagging Regressor, and Extra Tree Regressor models to forecast the li-ion battery life for electric vehicles. Using actual battery data from Hawaii National Energy Institute (HNEI), four algorithms were used to forecast remaining useful life (RUL) of batteries. These algorithms were implemented using Python in Google Co-laboratory. The accuracy of each model, Performance error indices including Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-squared, and computational time were calculated. Findings show that Bagging Regressor model outperforms the other three models in terms of RUL prediction. The Bagging Regressor model demonstrated its superiority with better *R*2 values of 0.999 and lower MSE of 14.307, RMSE of 3.782, and MAE of 2.099. The proposed model enhances EV energy management through precise RUL forecasting.

I. INTRODUCTION

Electric vehicles (EVs) have become more commonplace since they were first developed decades ago as a means of mobility. EVs provide unparalleled benefits over gas-powered cars, including rapid acceleration, virtually silent operation, and little emissions. With the growing use of electric cars, portable consumer electronics, and grid-tied energy storage systems for load balancing and energy storage technologies are becoming more and more common [1], [2]. Currently, the main energy source for EV's is lithium-ion batteries. Lithium-ion battery usage is pervasive in several industrial applications. Decreased performance is one of the major consequences that might result from a battery failing [3]. The complex combinations of materials construct lithium-ion battery packs used in EVs provide the energy and power required for operation.

Remaining useful life (RUL) is a strategic tool that helps determine how much capacity a system can supply at any given moment before it fails or is decommissioned. It aids professionals in design and administration of systems to prevent unforeseen malfunctions, which can be expensive to maintain [4]. It is a method that assesses if a project's mission goals are realistic and aids in the real-time diagnosis, prognosis, and fault detection of issues while taking uncertainties into account. PHM dependability and safety of battery systems depend on accurate RUL prediction. A battery's reserve capacity RUL is the maximum number of cycles through which it may be charged and discharged before it reaches end of life (EOL). Where EOL typically denotes the point at which

a battery's capacity drops to less than 70–80% of its stated capacity. Remaining Useful Life prediction calculated as,

$$RUL=T_{EOL}- T_{CU} \quad (1)$$

T_{EOL} stands for the amount of time a battery may be used. Battery current utilisation time is abbreviated as T_{CU}. The first equation considers calendar ageing in addition to cycle ageing. Most studies define the RUL purely in terms of cycle aging. Another definition that is applicable to RUL is as follows:

$$RUL= \frac{N_i-N_{EOL}}{N_{nominal}-N_{EOL}} \quad (2)$$

where N_i is present capacity, $N_{nominal}$ is the nominal capacity and N_{EOL} end-of-life capacity respectively.

As we stand at the intersection of technological innovation and sustainable energy practices, the incorporation of machine learning algorithms into LIB RUL cycle prediction seems like a revolutionary step towards a future where energy storage systems are not only powerful but also environmentally conscious and commercially viable. "Consequently, numerous approaches to RUL prediction have been developed by academics, which can be broadly categorized into two categories: model-based and data-driven. Recent advancements and successes in machine learning (ML) approaches have led to increased interest in the state estimation of LIB incorporating RUL." [5].

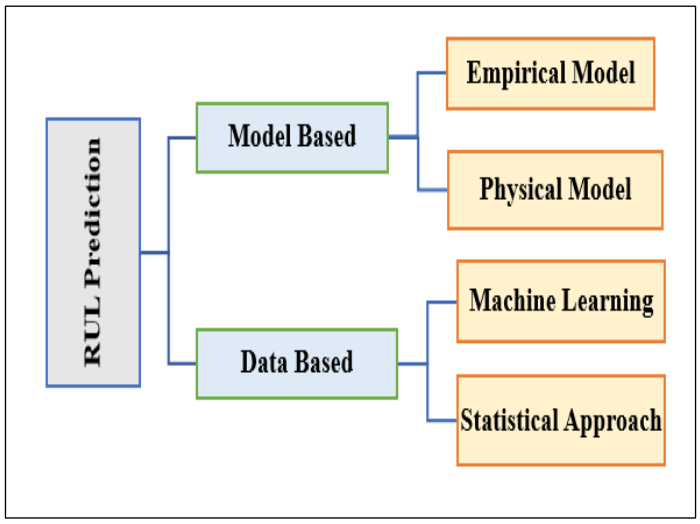

Figure 1: RUL Prediction Classification.
Source: Authors, (2025).

The degradation pattern of batteries might be well described by model-based prediction techniques. However, for precise prediction and deterioration modelling, a lot of variables and intricate computations are frequently needed. Because of this, the model is unsuitable for real-time prediction and practical implementation. There are two main types of model-based predictions: empirical and physical. Use of an empirical model for RUL prediction is employed by a number of battery degrading properties. To represent the degradation behaviour, empirical approaches utilise various regression models. To anticipate the degradation trend, they use empirical formulas. In [6], the authors demonstrated the efficacy of a logarithmic model-based RUL prediction framework compared to more conventional empirical models. An explanation based on physical and electrochemical processes within the battery is the basis of the physical model [7]. The physics model for RUL prediction is built using concepts of electrode porosity and reaction kinetics.

Data-driven techniques may be roughly categorized as machine learning (ML)-based and statistically-based. Artificial intelligence (ML) techniques employ external battery factors to forecast the health of the battery, making them simpler to implement and frequently reducing the need for precise battery modelling and domain-specific expertise. [8] Usually, the ML algorithms monitor changes in internal resistance, impedance, voltage, capacity, and computational efficiency to determine the deterioration trend for RUL prediction. The model of capacity deterioration is derived from previous data is Statistical modelling may be used with accuracy and ease. [9] The statistical techniques used for predicting Remaining Useful Life (RUL) include Autoregressive approach and Grey Prediction Model. This study made use of bagging, extra-tree, K- nearest neighbor and gradient boosting regression models. Based on performance metrics, four models will be tested to estimate lithium-ion battery RUL capacity. There is an explanation of the four regression models' efficacies executed on HNEI battery data set.

The following is the outline of the article. A survey of relevant literature is provided in Section 2, while Section 3 details methodology and four different ML regression techniques. In Section 4, we offer the results together with our assessment of them. Section 5 draws conclusions.

II. LITERATURE REVIEW

The growing number of electric vehicles has resulted in a significant problem for the infrastructure, electrical system, and charging station requirements. Electric vehicles often use LIBs, which are electrochemical systems that are dynamic, time-varying, and exhibit complex internal mechanics and nonlinear behaviour. The LIB's life and performance steadily decline with charge and discharge cycles. De-gradation of batteries can occur for a variety of causes, such as temperature fluctuations, mechanical stress, chemical reactions, and changes in physical processes. Predicting the battery's remaining lifespan also becomes a very difficult process as a result of deterioration. Still, in order to guarantee dependable performance of the battery management system, this is necessary.

It will be helpful to compare performance of data-driven and physical modelling techniques with the same battery and operational parameters. Battery SOH and RUL prediction may be accomplished with an accurate model, ensuring the safety of using EV batteries [10]. Battery remaining useful life prediction and performance indices of ML algorithms were studied in [11] The obtained findings indicate that the random forest technique was more appropriate for accurate RUL prediction. The duration between the present observation and end of battery's life is defined by the manufacturer as Remaining Useful Life (RUL) [12]. In [13] employed a segmentation-type anomaly detection technique utilizing temperature and voltage measurements taken at several timesteps to determine how the Li+ battery's properties were changing. Therefore, to estimate the battery's RUL, the Extra Tree Regression (ETR) approach may be employed to extract important variables from temperature and voltage transitions, including variance, kurtosis, skewness, and voltage. In this [14], applied, and examined three machine learning models, including SVR and LSTM Network and also examined the impact of calendar aging on a battery's RUL. The purpose of these two sets of trials was to strengthen RUL prediction models by including calendar aging effects. This study used three regression models based on

supervised machine learning predict life span of LIB. [15] Models based on voltage-dependent per-cell data will be used to compare LR, BR, and RFR in estimating capacity of batteries. [16] paper discusses difficulties in estimating the battery life cycle using machine learning and outlines potential avenues for further study and improvement, including scalability, interpretability, and the integration of upcoming technologies. With a comprehensive introduction to BMSs and ML, this [17] study examines latest results on ML methods for SOC prediction. This paper highlights the common use of many techniques in predicting SOC and SOH, including support vector machines, fuzzy logic, k-nearest neighbors, genetic algorithms, and transfer learning. [18] RUL prediction of batteries, Gradient Boosting (GB) and Naive Bayes (NB) algorithms are recommended. The battery's performance parameter is maximized by doing an error analysis on the model. Selecting statistical metrics allows for a quantitative assessment of forecast results.

III. METHODOLOGY

III.1. METHODOLOGICAL FRAMEWORK

Figure. 2 shows the basic Remaining useful life prediction methods based on machine learning for LIB. Most recently developed machine learning based prediction techniques are covered in next
section.

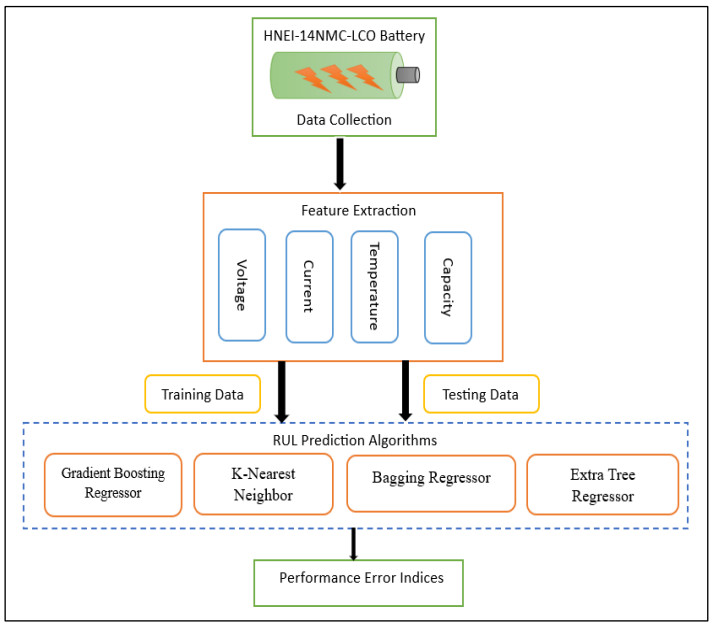

Figure 2: Framework of RUL prediction technique.
Source: Authors, (2025).

A typical machine learning approach for forecasting a battery's RUL is depicted in figure 2. Gathering data, extracting features, training models, and evaluating them are all part of it.

Data Collection: The procedure starts by gathering data from the battery, including factors such as voltage, current, temperature, and capacity.

Feature Extraction: Collected data is further processed to extract relevant features that will be utilized for training and testing the RUL prediction.

Training Data: Used to train the RUL prediction algorithms.

Testing Data: Evaluate the performance of trained models.

RUL Prediction Algorithms: GBR, KNN, BR and ETR are the ML algorithms used for prediction.

Performance Error Indices: The performance of each RUL prediction algorithm is evaluated using error indices. These indices help determine how well each algorithm predicts the RUL of the battery.

III.2. PROPOSED ALGORITHMS:

III.2.1. Gradient Boosting Regressor (GBR):

As an optimization technique, gradient descent trains successive models to minimize a loss function, such cross-entropy relative to its predecessor [19]. Combining several weak models into one strong predictive model is the goal of gradient boosting, an effective ensemble approach. The following figure shows the steps involved in training gradient-boosted trees to solve regression problems.

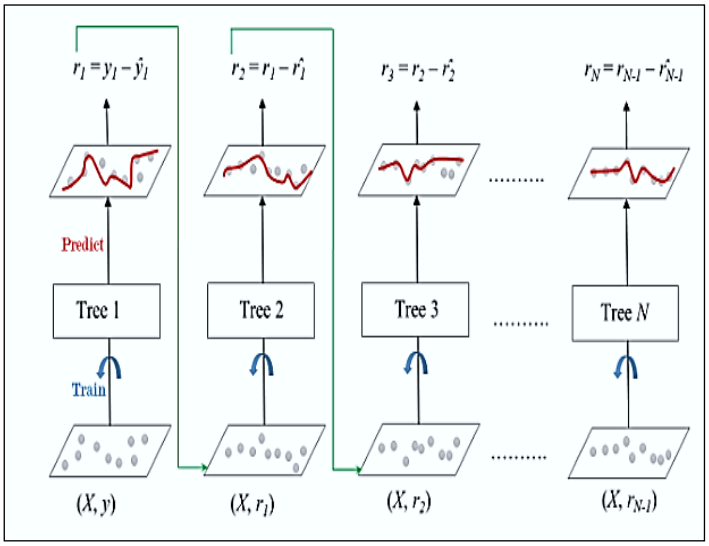

Figure 3: Training of Gradient Boosting Regressor.
Source: Authors, (2025).

The set of 'N' trees is derived from the illustration. For Tree1's training, we utilize 'y' and feature matrix 'X'. Predictions labelled $\hat{y}_1$ are used to find the training set residual errors, r_1.Next step is to train Tree2 using 'X' as feature matrix and labels from r1, residual errors of Tree1. We next determine residual r_2 by use the expected results, $\hat{r}_1$.

We keep doing this until we've trained all 'N' trees in our ensemble. One of the most important parameters used by this strategy is shrinkage. The term "shrinking" describes the effect of multiplying the predictions of each ensemble tree by the learning rate, eta, which can take values between zero and one. There is a trade-off between eta and the number of estimators; a lower learning rate necessitates a higher number of estimators to preserve a certain model performance. The formula below gives the final forecast, after each tree has made a label prediction.

$$y(p) = y_1 + (H * r_1) + (H * r_2) + . + (H * r_n) \quad (3)$$

Algorithm:

Step 1: Let's assume that the input and target, X and Y, consist of N samples each. Main objective is to determine function f(x) that maps input characteristics X to target variables y. It represents the cumulative number of trees that have been reinforced. The difference between expected and observed values quantified by loss function.

$$L(f) = \sum_{i=1}^{N} L(y_i, f(x_i)) \quad (4)$$

Step 2: Minimize loss function L(f).

$$f_0(x) = argmin_f L(f) = argmin_f \sum_{i=1}^{N} L(y_i, f(x_i)) \quad (5)$$

Step 3: Gradient descent
For 'M' stage gradient boosting gradient descent finds

$$h_m = -\rho_m g_m$$

$$g_m = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right] \quad (6)$$

Step 4: Prediction
The gradient Similarly for trees:

$$f_m(x) = f_{m-1}(x) + (argmin_{hm}(argmin_{hm}\left[\sum_{i=1}^{N} L(y_i, f_{m-1}(x_i) + h_m(x_i)\right](x) \quad (7)$$

The final solution is:

$$f_m = f_{m-1} - \rho_m g_m \quad (8)$$

III.2.2 K-Nearest Neighbor (kNN)

It uses similarities between new data points and old data to determine their classification. It operates under assumption that similar data points are located close to each other in feature space. By storing all training data, KNN can efficiently assign new data points to the most appropriate category based on their proximity to known data points. Despite its popularity in the classification domain, KNN has a place in regression analysis as well. The core idea is to classify a testing point based on its nearest neighbors in feature space, where k is a given integer. This neighborhood is selected from a set of training points whose correct classifications are known. Due to its laziness as a learning algorithm, kNN only uses approximations at the local level to approximate functions, saving computation until when it is truly necessary [20]. The nearest training points (K(1), K(2),..., K(n)) in a neighborhood are weighted to provide an estimate of the answer (xt) for a testing point (xt) in a k-nearest neighbor regression. It is common practice to use a kernel function that takes into account the distance between each neighbor and the testing point to calculate their weight.

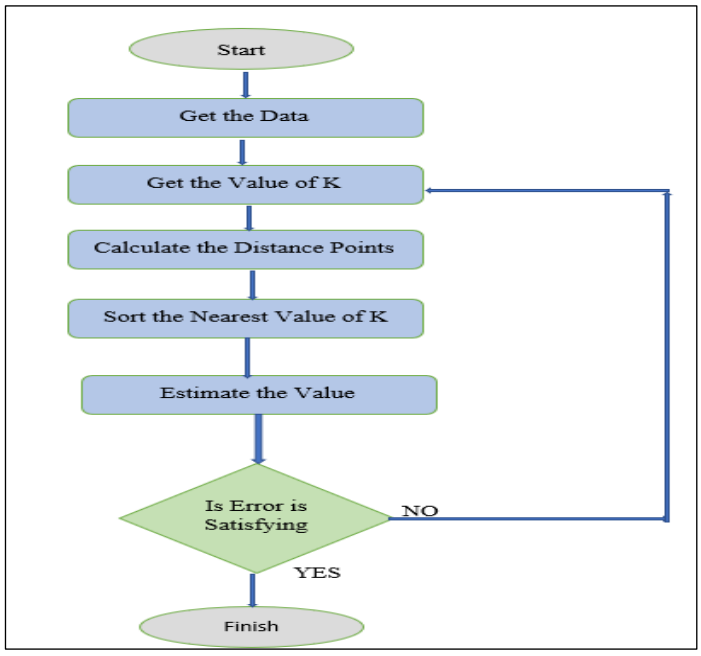

Figure 4: Flow chart for KNN.
Source: Authors, (2025).

Let K = {k1, k2,..., kM} be a training data set with M training points and N features per training point. weighted Euclidean distance, represented as,

$$KNN = d(K_t, K_i) = \sqrt{\sum_{n=1}^{N} w_n (k_{t,n} - k_{i,n})^2} \quad (9)$$

3.2.3. Extra Tree Regressor (ETR)

Developed as an extension of the Random Forest (RF) model by Geurts et al., Extra Tree Regressor (ETR) [21] describes a considerable enhancement to ensemble learning. A collection of unpruned regression trees, each produced by a standard top-down algorithm, form the basis of the ETR method. This method uses a two-stage procedure for regression analysis, namely bootstrapping and bagging, which is different from the RF model. Whenever a tree is being trained in the ETR model, a deterministic splitting method is used. Although RF uses a selection technique to find the best split from a random set of attributes at each node (as shown in the image below), ETR picks the best split from these options by randomly picking a split point for every feature.

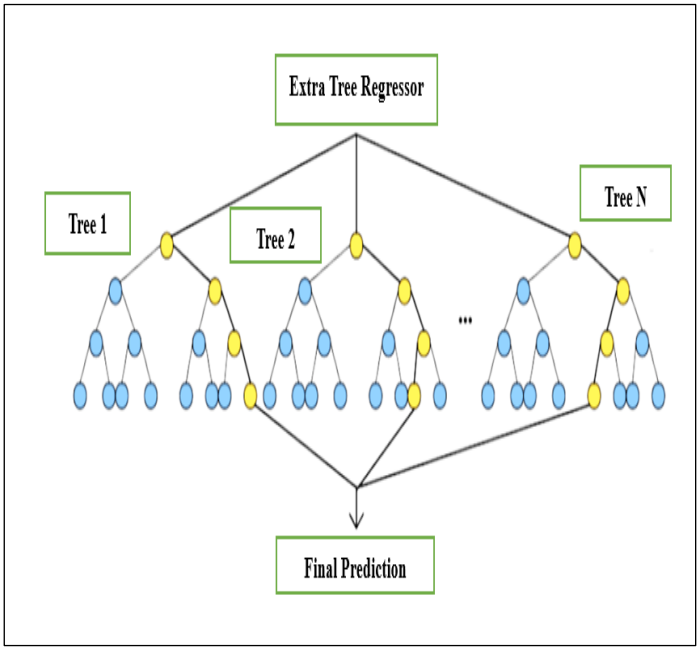

Figure 5: Extra Tree Regressor.
Source: Authors, (2025).

Here is the mathematical representation:

$$X_{ETR} = Arg_{n,\,m}\ min[Error(n,m)] \quad (10)$$

The variable X_{ETR} indicates the split that was decided in the ETR method in this example. An attribute is represented by the letter 'n', while a randomly chosen feature split point is symbolized by the number 'm'.
The split's success in reducing errors is determined by the function Error (n, m). In order to reduce this mistake, the algorithm chooses a n and m value. Typically, the final forecast is computed as an average of the votes cast by each tree during the bagging step of the RF method. But the ETR method uses a broader set of unpruned trees in a comparable fashion. For a brief mathematical description of the output from the ETR model, see the equation below.

$$Y_{ETR} = \frac{1}{N}\sum_{i=1}^{N} T_i(X) \quad (11)$$

The input feature vector is X, and the output is Y_{ETR}.

3.2.4. Bagging regressor (br)

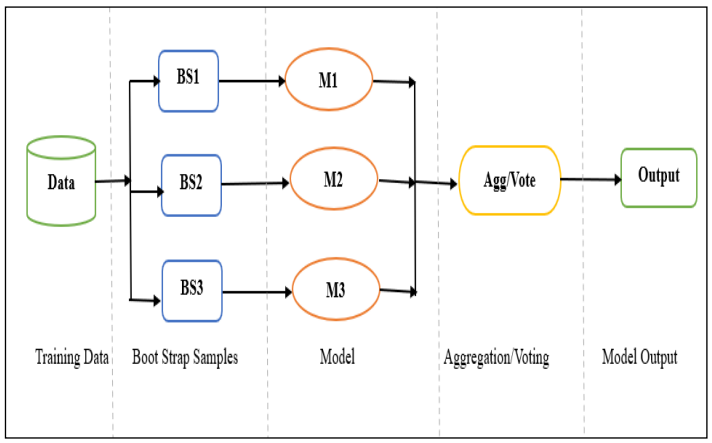

Figure 6: Bagging Regressor Algorithm.
Source: Authors, (2025).

Ensemble learning is a method in supervised machine learning where many models are combined to create a more powerful single model. As an ensemble learning method, "bagging" or "bootstrap aggregating" entails training many base models concurrently on different subsets of training data [22].

Bootstrap sampling, which selects data points at random replacement, is used to create each subgroup. For the bagging classifier, majority voting is used to aggregate the all-base model's predictions to arrive at the final prediction. In order to get at a final prediction, regression models average the predictions from all of the base models, a process known as bagging regression. The Bagging Algorithm, as seen in Figure 6 below, consists of many phases.

Training Data: Data is selected for training form available datasets.

Boot Strap: Randomly chosen "n" subsets of the initial training data are selected with replacement in the bootstrap sampling method. While certain samples may appear more than once in the new subset while others may be excluded, this process guarantees that basic models are trained on variety subsets of data. It raises model's accuracy and lowers the danger of overfitting.

Model: Involves creating a separate subset of data for each base model, which is trained independently using a specific approach . Due to their potential lack of accuracy when used alone, these models are commonly known as "Weak learners." As the basic model does not utilize separate data subsets during training**.**

Aggregation/Voting: The majority vote determines the anticipated class label in the bagging classifier for given instance. The class predicted by the model is the one with the majority of votes.

Model Output: Bagging generates a final forecast for each instance by combining the predictions from all of the underlying models. Bagging regressor provides a potent way to boost model resilience and predictive performance. By using the collective knowledge of several base models, the Bagging regressor prevents overfitting, enhances generalization, and provides reliable predictions for a broad range of applications.

IV. RESULTS AND DISCUSSION

IV.1. DATA SET

Fourteen NMC-LCO 18650 batteries, with a nominal capacity of 2.8 Ah each, make up the dataset utilised for forecasting the Remaining Useful Life. [23] The batteries were tested by the Hawaii Natural Energy Institute through over a thousand cycles at a temperature of 25°C.A 1.5 C discharge rate and a C/2 CC-CV charge rate were utilised in the tests. The information includes important statistics about voltage and current, which essential required for calculating the batteries' remaining useful life (RUL).

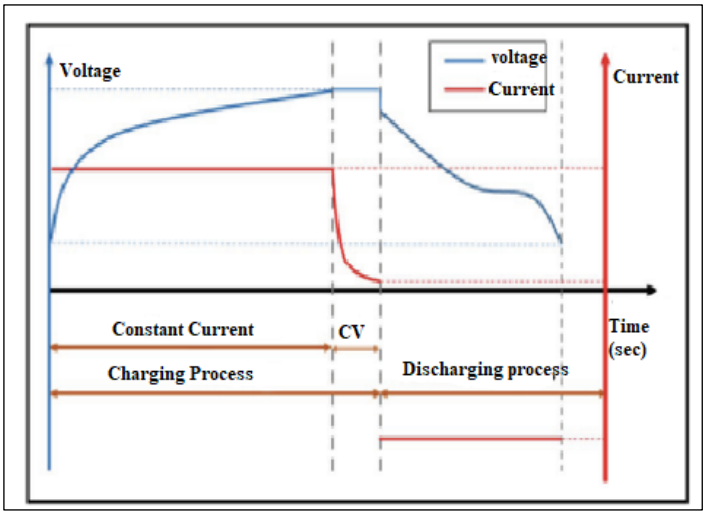

Figure 7: Charging and Discharging of LIB's..
Source: Authors, (2025).

IV. MODEL VALIDATION

Multiple techniques exist for assessing the efficacy of models. This study utilizes four statistical measures, namely MAE, MSE, RMSE, and R2, to evaluate performance of models. Evaluative metrics are shown in the following equations (12–15).

$$MAE = \sum_{i=1}^{n}(x_i - y_i) \quad (12)$$

$$MSE = \sum_{i=1}^{n}\frac{(x_i - y_i)^2}{n} \quad (13)$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(x_i - y_i)^2}{n}} \quad (14)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{y}_i)^2} \quad (15)$$

Where $x_i$represents the predicted value,y_i represents the observed value, $\bar{y}_i$ is the mean observed value, and n is the sample size.

IV.3 ASSESSING THE SUGGESTED MODELS' EFFECTIVENESS

We performed several necessary measures to make the dataset more amenable to examination and modelling. Data cleaning to remove errors, feature selection to provide useful information about battery behaviour, feature creation to add more insights, data normalisation to make sure all features are on same scale, categorical variable transformation to modellable format, data split into training and testing sets to evaluate model performance were all part of this project.

There are 15,065 rows and 9 columns in dataset. Training uses 70% of the data, while testing uses the other 30%. By dividing dataset, model may be trained on a bigger dataset for training and tested on a smaller one.

Table 1: Performance Model Validation of RUL prediction using Machine Learning Algorithms.

Algorithms	MSE	RMSE	MAE	R^2	Time
Gradient Boosting	53.941	7.344	4.837	0.976	0.722
K Nearest Neighbor	57.061	13.109	9.721	0.988	0.820
Bagging Regressor	14.307	3.782	2.099	0.999	0.124
Extra Tree Regressor	30.763	5.546	2.523	0.997	0.138

Source: Authors, (2025).

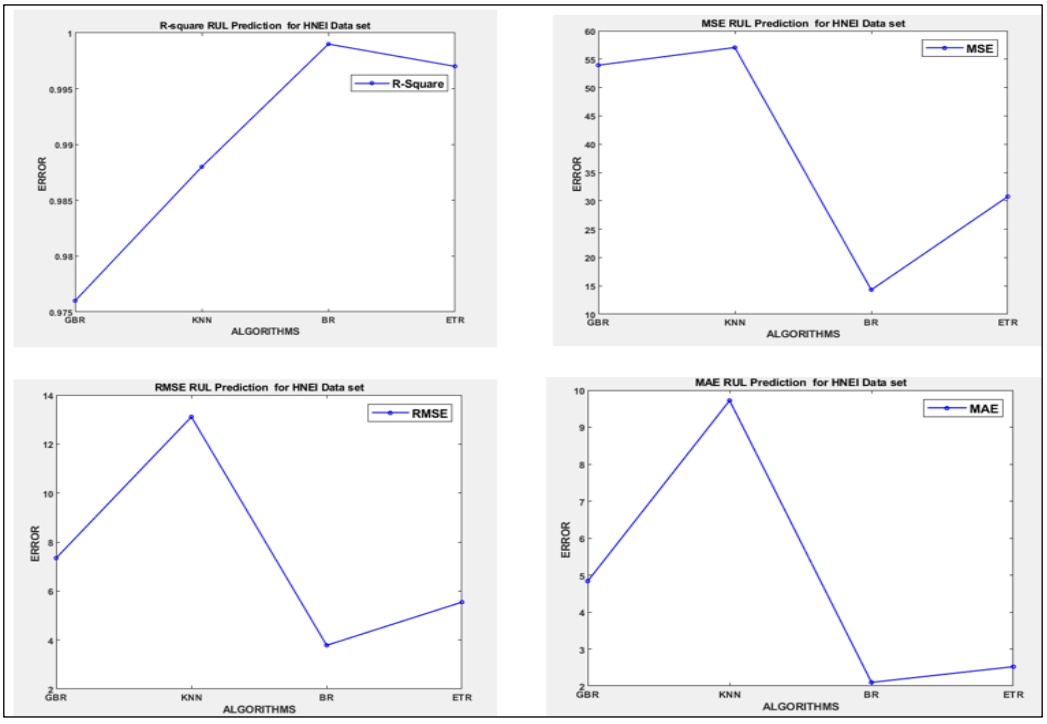

Figure 8: Estimation results of the HNEI aging dataset.
Source: Authors, (2024).

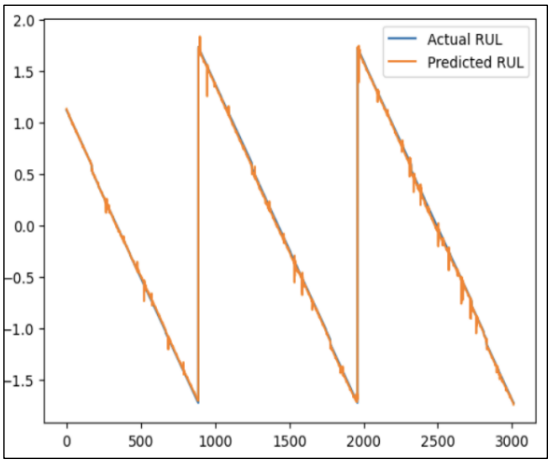

Figure 9(a): RUL Actual Vs Predicted.

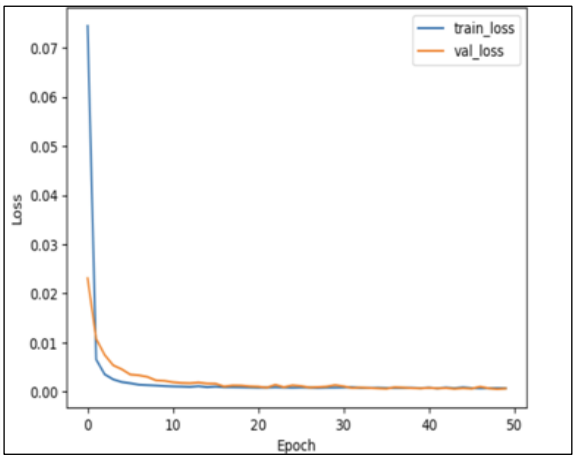

Figure 9(b):Training and validation loss.
Source: Authors, (2025).

The effectiveness of machine learning models, GBM, KNN, BR and ETR in forecasting battery RUL is compiled in Table 1. The efficiency of models was evaluated using metrics, including MAE, MSE, RMSE and R2 with its execution time.

From the performance model validation Table 1 it indicates that bagging regressor model performs better than the other types, according to the data.

With an R2 value of 0.999. BR model has best prediction accuracy, surpassing GBR, KNN, and ETR, as shown by its lowest RMSE of 3.782. A MAE of 2.099 confirms that the BR model accurately estimates the target variable.

The accuracy of the BR model's estimation of RUL for the HNEI technique is shown in Figure 8. The results demonstrate that, when applied to the HNEI aging dataset, the proposed BR model estimates RUL for a variety of performance error indices with robustness and accuracy. The proposed models demonstrated strong performance and increased forecast accuracy. The suggested BR technique has the potential to significantly increase a lithium-ion battery's RUL prediction accuracy.

Figure 9(a) presents a clear comparison between the real Remaining Useful Life (RUL) values and the anticipated RUL values generated by our model for the most recent 100 test samples.

The x-axis depicts the indices of the most recent 100 test samples, providing a historical perspective on the prediction performance over time. Every data point on the diagram represents a singular test sample. The y-axis represents the RUL values, which measure the remaining useful life for each test sample.

The actual Remaining Useful Life (RUL) line represents the genuine RUL values obtained from the test data. It acts as a standard for assessing the model's ability to accurately estimate the Remaining Useful Life (RUL) of the systems being evaluated. The blue data points in Figure 9(b) represent the actual Remaining Useful Life (RUL) values, whereas the orange data points represent the predictions made by our model.

Significantly, there is a strong correlation between our predictions and the actual data at several places, demonstrating the model's efficacy.

IV.4 HEATMAP

Understanding the variables influencing battery life and performance can be aided by using heatmap to show the correlations between various battery system variables. Based on the heatmap in Figure 10, the following inferences can be made:

- Correlation coefficients: range from -1 to 1.
- Charging time and Discharge Time Correlation is 0.94, indicating that these variables are strongly positively correlated.
- Time at 4.15V and Charging time Correlation is 0.68, showing a moderate positive relationship.
- Using 0.78 coefficient, RUL and Maximum Voltage Discharge exhibit robust positive association.

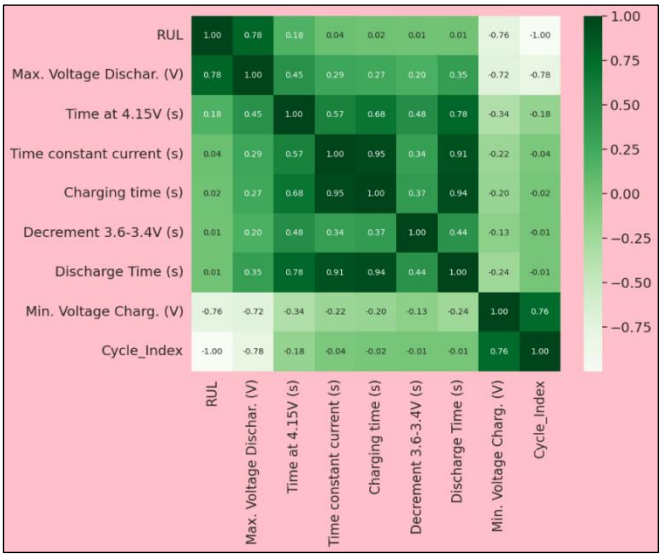

Figure 10: Heat map representing dataset characteristics.
Source: Authors, (2025).

IV.5 PERFORMANCE VALUATION OF MODELS IN COMPARISON TO RELATED MODELS

A comparison of performance evaluation values for several battery RUL prediction techniques is shown in Table 2. Our models' values are compared to all previous approaches. These results show the remarkable accuracy and precision of our approach, underscoring its potential for accurate RUL prediction and ensuring the stable and efficient functioning of LIB in many applications.

'The table prominently presents important assessment measures, including RMSE. In table 2 comparison of proposed model's expected outcomes with those of previous methods. MAE in addition to the R2. Lower numbers indicate more accuracy in terms of predictive precision, as measured by RMSE and MAE. Notably, our suggested methods offering deep insights into its exceptional predictive powers. This outcome demonstrates the higher predictive ability of models in comparison to alternative battery RUL prediction techniques.

Table 2: Comparison of Performance error indices for RUL prediction with different models.

Referance	Model	MSE	RMSE	MAE	R-Square
[11]	GBR	57.447	7.579	4.984	-
	LR	54.543	7.385	4.644	-
[13]	ETR	98.031	9.788	-	-
[15]	BR	516.332	22.72	-	-
[18]	GBR	54.433	7.853	-	-
[20]	KNN	-	8.274	7.623	0.995
Proposed	**BR**	14.307	3.782	2.099	0.999

Source: Authors, (2025).

V. CONCLUSION

This research suggests four different regression models like Gradient Boosting Regressor, K-Nearest Neighbor Regressor, Bagging Regressor, and Extra Tree Regressor models to forecast RUL prediction of LIB life for electric vehicles using real-life battery dataset from Hawaii Natural Energy Institute. Battery dataset's error metrics, such as R-Squared, MAE, RMSE, and MSE, were then ascertained. The four approaches all showed a noticeable variation in relevance when examined using various performance error indexes. The results show that BR method is capable of accurately and effectively determining RUL of batteries when compared with other GBR, KNN and ETR methods. For real-time prediction, the calculation time is also reasonable. Future research concentrates on applying Hybrid Learning methods to improve forecast accuracy.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Sravanthi C L and Dr.J N Chandra sekhar
Methodology: Sravanthi C L and Dr.J N Chandra sekhar
Investigation: Sravanthi C L and Dr.J N Chandra sekhar
Discussion of results: Sravanthi C L and Dr.J N Chandra sekhar
Writing – Original Draft: Sravanthi C L
Writing – Review and Editing: Sravanthi C L
Resources: Dr.J N Chandra sekhar
Supervision: Dr.J N Chandra sekhar

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