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Accurate RUL prediction of EV batteries using random forest and ensemble learning frameworks

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ABSTRACT

Precise remaining useful life (RUL) estimation for lithium-ion batteries is essential for improving the safety, reliability, and maintenance of electric vehicles (EVs). This study proposes a random forest (RF)-based ensemble learning framework using the publicly available Hawaii Natural Energy Institute (HNEI) dataset containing 15,064 charge–discharge cycles. Seven degradation-related features, including cycle index, discharge time, voltage decrement, maximum discharge voltage, minimum charging voltage, time at 4.15 V, and constant-current charging duration, are extracted to characterize battery aging. The proposed RF model is compared with linear regression (LR), long short-term memory (LSTM), and attention-LSTM models using MAE, root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). RF demonstrates superior prediction performance, achieving MAE of 5.20, RMSE of 6.83, MAPE of 1.33%, and R^2 of 0.997. Parity and residual analyses further confirm its strong predictive consistency. The proposed approach provides an accurate, computationally efficient, and interpretable solution for BMS applications, enabling effective battery health monitoring, predictive maintenance, charging optimization, and timely replacement.

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1. INTRODUCTION

The rapid electric vehicle (EV) adoption has increased the requirement for trustworthy and high-performance energy-storage systems. Lithium-ion batteries are widely preferred because of their high density of energy, long cycle life, low self-discharge, and good charging efficiency. However, repeated charge–discharge operation causes progressive degradation, including capacity loss and increased internal resistance, which ultimately reduces battery performance and service life. Battery aging is affected by temperature, charging/discharging rate, cycling history, and other operating conditions, leading to nonlinear and complicated deterioration behavior. Therefore, accurate remaining useful life (RULF or sophisticated battery management systems (BMSs) to function better, prediction is crucial battery safety, condition monitoring, maintenance planning, and EV reliability [1]-[5].

Data-driven machine-learning methods have gained significant attention for battery remaining useful life (RUL) prediction because they can learn nonlinear degradation relationships directly from measured battery data. Techniques such as random forest (RF), XGBoost, support vector regression, ensemble learning, long short-term memory (LSTM), and hybrid deep-learning models have demonstrated promising performance in battery SOH and RUL estimation [6]-[12]. Recent studies have also emphasized interpretable machine learning using approaches such as SHAP and explainable ensemble models, enabling better understanding of the factors influencing battery degradation predictions [13]-[15]. Nevertheless, complex deep-learning models can require large datasets, extensive hyperparameter optimization, and considerable computational resources. These limitations motivate the development of accurate and computationally efficient learning frameworks suitable for practical BMS implementation [16]-[20].

In this study, a random forest-based ensemble learning framework is developed for lithium-ion battery RUL prediction using the publicly available Hawaii Natural Energy Institute (HNEI) dataset containing 15,064 charge–discharge cycles. Seven degradation-related features, namely cycle index, discharge time, voltage decrement between 3.6 and 3.4 V, maximum discharge voltage, minimum charging voltage, time at 4.15 V, and constant-current charging time, are selected to characterize battery aging. The proposed RF model is compared with linear regression (LR), LSTM, and attention-LSTM using mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and R^2 as evaluation metrics. Parity plots and residual analysis are additionally employed to assess prediction consistency [21]-[23]. The study demonstrates that an ensemble-learning approach can provide a practical balance among prediction accuracy, computational efficiency, and interpretability, supporting battery health monitoring, predictive maintenance, charging management, and timely battery replacement in EV applications [24], [25].

2. PROPOSED DYNAMIC APPROACH

With the growing uptake of electric vehicles (EVs), it has become crucial to accurately predict the RUL in order to enhance battery reliability and safety, as well as to optimize maintenance planning. Batteries with lithium ions exhibit nonlinear degradation due to varying operating conditions, making conventional prediction methods less effective. Therefore, this work proposes an ensemble learning framework for RUL prediction using the Hawaii Natural Energy Institute (HNEI) battery dataset. Four prediction models linear regression, random forest, LSTM, and LSTM with attention are developed and compared to identify the most accurate approach. Random forest achieved the best performance with MAE = 5.20, RMSE = 6.83, and MAPE = 1.33%, outperforming the deep learning models by effectively capturing nonlinear degradation patterns [10]-[12]. The proposed framework supports intelligent battery management systems (BMSs), extends battery lifespan, and enhances EV sustainability. Figure 1 shows the framework for EV battery RUL prediction.

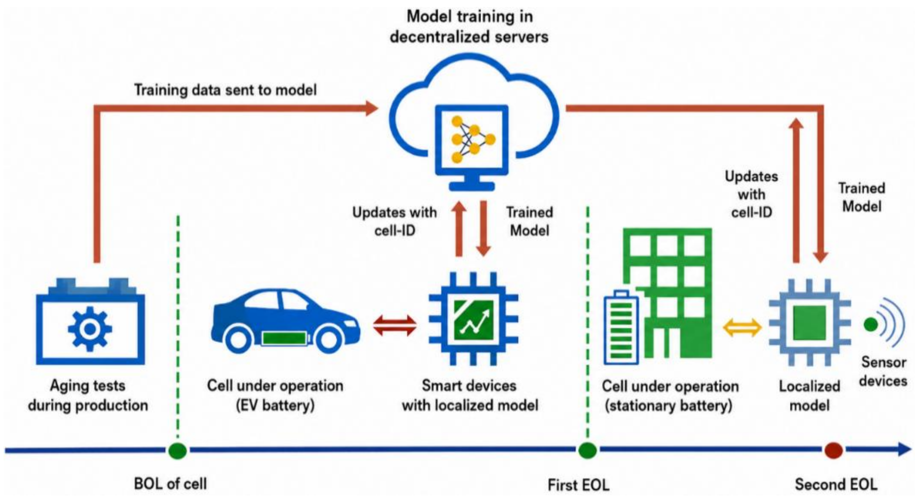

Figure 1. Proposed framework for EV battery RUL prediction

2.1. Proposed framework and battery degradation analysis

The proposed framework estimates the RUL of lithium-ion batteries using an ensemble learning approach. The methodology involves HNEI dataset acquisition, data preprocessing, feature extraction, normalization, model training, and performance evaluation. The dataset contains approximately 15,064 charge–discharge cycles obtained from 2.8 Ah NMC lithium-ion cells under controlled conditions. Seven degradation indicators—cycle index, discharge time, voltage decrement between 3.6–3.4 V, maximum discharge voltage, minimum charging voltage, time at 4.15 V, and constant-current charging time are selected to represent battery aging. Missing and duplicate records are removed, outliers are examined, and the numerical features are normalized using Min–Max scaling. The processed data are divided into 80% training and 20% testing subsets. These features capture the progressive changes associated with battery degradation and are therefore used as inputs for RUL prediction. Figure 2 illustrates the HNEI RUL Prediction. The Min–Max normalization is expressed as (1).

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

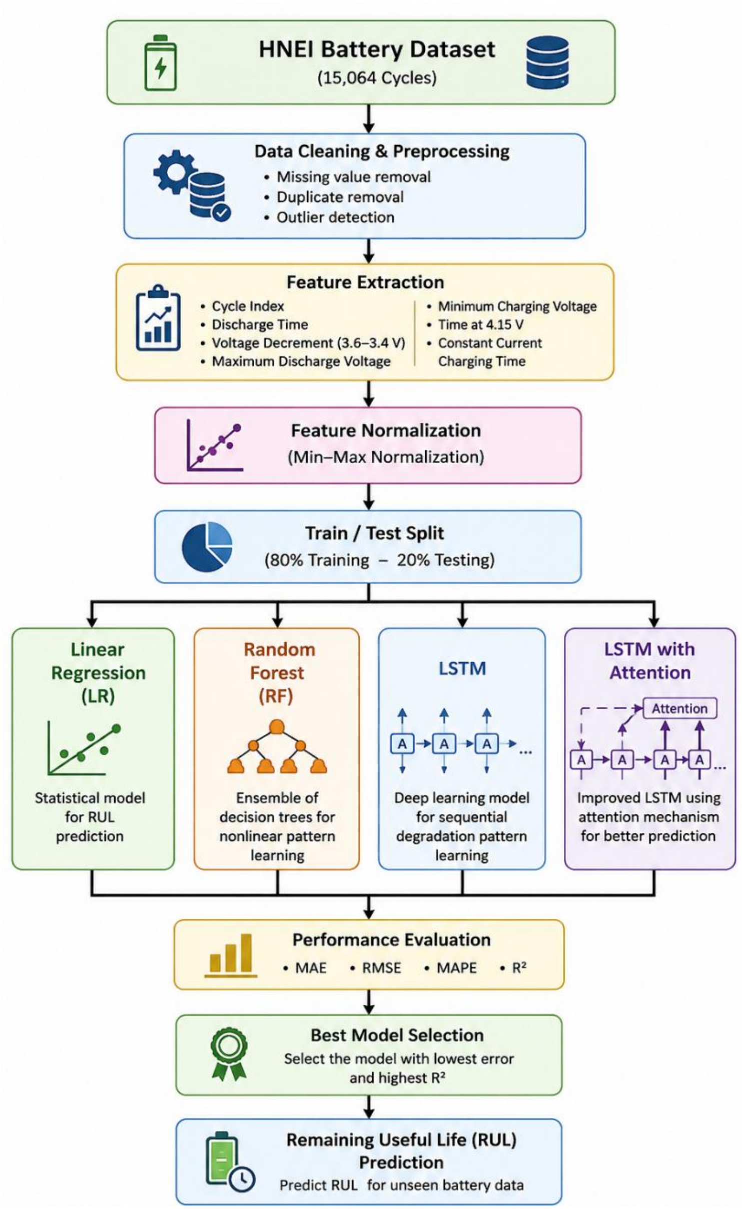

Figure 2. Proposed framework for HNEI RUL prediction

2.2. Random forest-based RUL prediction

Random forest is an ensemble learning method that integrates several regression trees using bootstrapping in order to enhance the accuracy of predictions and mitigate overfitting. Every decision tree is trained using randomly selected samples and input features, and the final RUL prediction is obtained by averaging the outputs of all trees.

$$\hat{Y} = \frac{1}{N}\sum_{i=1}^{N} T_i\,(x) \tag{2}$$

The optimized hyperparameters used for the random forest model are presented in Table 1.

The selected hyperparameters enabled the Random Forest model to effectively capture the complex and nonlinear patterns associated with battery degradation. By optimizing the model parameters, a balance was achieved between high prediction accuracy and computational efficiency. The model was able to identify important relationships among various battery parameters that influence the degradation process and remaining useful life (RUL). As a result, the random forest model provided more accurate and reliable RUL predictions compared with the traditional linear regression approach. It also demonstrated better overall performance than the LSTM and LSTM with attention models in predicting battery health and degradation trends. Therefore, the proposed Random Forest model is considered a promising and computationally efficient approach for practical implementation in battery management system (BMS) applications.

Table 1. Random forest hyperparameters

Parameter	Value	Purpose
Number of trees	200	Improves prediction stability
Maximum depth	20	Controls model complexity
Bootstrap	True	Enables bagging for better generalization
Maximum features	√Features	Reduces tree correlation
Minimum samples split	2.1	Allows effective node splitting
Random state	43	Ensures reproducible results

2.3. Model validation and performance evaluation

The developed prediction models were assessed with the MAE, RMSE, MAPE, and the coefficient of determination (R2). Lower MAE, RMSE, and MAPE values together with higher R^2 indicate better prediction performance.

$$\mathrm{MAE} = \frac{1}{N}\sum_{\mathrm{j}=1}^{N}\left|\mathrm{j} - \hat{Y}_j\right| \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{\mathrm{j}=1}^{N}\left(Y_j - \hat{Y}_j\right)^2} \tag{4}$$

$$\mathrm{MAPE} = \frac{100}{N}\sum_{j=1}^{N}\left|\frac{Y_j - \hat{Y}_j}{Y_j}\right| \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{N}(Y_i - \bar{Y})^2} \tag{6}$$

Model validation was carried out using parity plots and residual error analysis to examine the accuracy and consistency of the prediction models. Among the evaluated approaches, the random forest model produced the best performance, with an MAE of 5.20, RMSE of 6.83, MAPE of 1.33%, and an R^2 value of 0.997. The parity plot showed that the predicted RUL values closely matched the corresponding measured values, indicating a high level of prediction accuracy. In addition, the residual errors were concentrated near zero with no noticeable systematic pattern, demonstrating stable model performance and a low level of prediction bias. These results confirm that the proposed ensemble learning framework provides reliable and robust RUL estimation, making it suitable for battery health monitoring, predictive maintenance, and practical BMS applications.

3. RESULTS AND DISCUSSION

The proposed battery RUL prediction framework was implemented using Python 3.10 with Scikit-learn, tensor flow/Keras, and NumPy libraries. The experiments were conducted on the Hawaii Natural Energy Institute (HNEI) lithium-ion battery dataset, which contains 15,064 charge–discharge cycles with seven significant degradation features. The extracted features include cycle index, discharge time, decrement (3.6–3.4 V), maximum discharge voltage, minimum charging voltage, time at 4.15 V, and constant current charging time. These parameters effectively represent battery aging behavior and provide sufficient information for accurate remaining useful life prediction.

Table 2 summarizes the statistical characteristics of the selected battery degradation features. The dataset consists of 15,064 battery cycles, with the cycle index ranging from 1 to 1134 cycles and an average value of 556.15 cycles, indicating that the dataset covers the complete battery degradation process. The discharge time varies considerably, with a mean value of 4581.27 s, while the charging-related features such as time at 4.15 V and constant current charging time also exhibit significant variations due to battery aging. The maximum discharge voltage has an average value of 3.908 V, whereas the minimum charging voltage averages 3.578 V, clearly reflecting the electrochemical degradation occurring during repeated charging and discharging cycles. These statistical observations confirm that the dataset contains sufficient variability for training reliable machine learning models for battery RUL prediction. The prediction performances of linear regression, random forest, LSTM, and LSTM with Attention were evaluated using MAE, RMSE, and MAPE. The comparative results presented in Table 2 and Figure 3 clearly demonstrate the superiority of the random forest model over the other prediction techniques.

Table 3 presents the performance comparison of the battery RUL prediction models using MAE, RMSE, and MAPE metrics. Among all the models, the Random Forest model achieved the lowest prediction errors, with an MAE of 5.20, RMSE of 6.83, and MAPE of 1.33%, demonstrating its superior accuracy in predicting battery RUL. Although the LSTM with attention model performed better than the conventional LSTM model, its prediction accuracy was still considerably lower than that of the random forest model. Similarly, the linear regression model showed higher prediction errors because it was unable to effectively capture the nonlinear degradation behavior of lithium-ion batteries. Figure 4 further illustrates the comparative prediction performance of the different battery RUL models.

Table 2. Statistical description of battery degradation features

Feature	Description/significance	Count	Mean	Std. Dev.	Min	50%	Max
Cycle index	Sequential number of charges–discharge cycles, indicating battery aging progression	15,064	556.155	322.378	1	560	1134
Discharge time (s)	Total discharge duration per cycle; reflects load and energy delivery efficiency	15,064	4581.27	33,144	8.69	1557.2	958,320
Decrement 3.6–3.4 V (s)	Time taken for voltage drop between 3.6–3.4 V during discharge; indicates degradation rate	15,064	1239.78	15,039.6	−397,646	439.24	406,704
Max. voltage discharge (V)	Peak voltage noted while discharging phase	15,064	3.908	0.091	3.043	3.906	4.363
Min. voltage charging (V)	Minimum voltage observed during charging phase	15,064	3.578	0.124	3.022	3.574	4.379
Time at 4.15 V (s)	Duration for which the cell voltage remained near 4.15 V during charging	15,064	3768.34	9129.55	−113.58	2930.2	245,101
Time constant current (s)	Charging duration under constant current mode	15,064	5461.27	25,155.8	5.98	3824.2	880,728

Table 3. Performance comparison of battery RUL prediction models

Model	MAE	RMSE	MAPE (%)
Linear regression	143.15	967.04	20.31
Random forest	5.20	6.83	1.33
LSTM	544.03	614.76	94.99
LSTM + attention	252.33	286.67	81.38

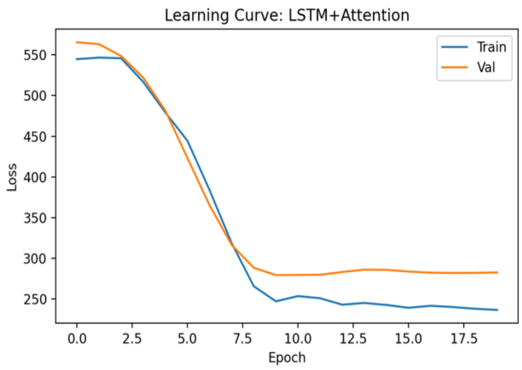

Figure 3. Learning curve of LSTM Mode

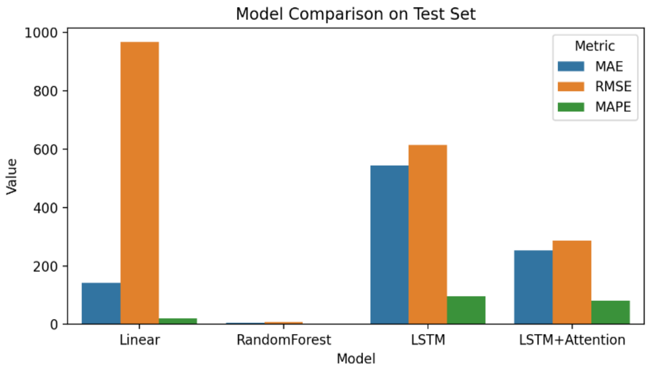

Figure 4. Comparison of prediction performance of battery RUL models

Figure 5 illustrates the training and validation loss curves of the LSTM model during the learning process. Both training and validation losses show a significant decrease during the initial epochs, indicating that the model is effectively learning the underlying patterns in the battery data. After approximately 10 epochs, the loss values gradually stabilize, demonstrating good convergence and consistent model performance. The small difference between the training and validation losses also suggests that the model has limited overfitting and maintains good generalization capability. Furthermore, the stable loss curves indicate that the LSTM architecture is suitable for capturing the temporal characteristics of battery degradation. Overall, the results presented in Figure 3 confirm the effective learning, convergence, and stability of the LSTM model for battery RUL prediction.

Figure 6 illustrates the comparison between the predicted and actual RUL values, where most of the predicted values closely follow the reference line, indicating good overall prediction accuracy. However, a few significant outliers can be observed, suggesting that the model experiences difficulty in accurately predicting certain battery degradation patterns. In contrast, Figure 7 shows poor agreement between the predicted and actual RUL values obtained using the LSTM model. The predicted values are largely concentrated near zero, indicating that the model is unable to effectively capture the actual variation in RUL values. This behavior results in a substantial prediction error and limited overall model accuracy. Therefore, the comparison between Figures 6 and 7 highlights the superior prediction performance of the model shown in Figure 6 over the LSTM model for battery RUL estimation.

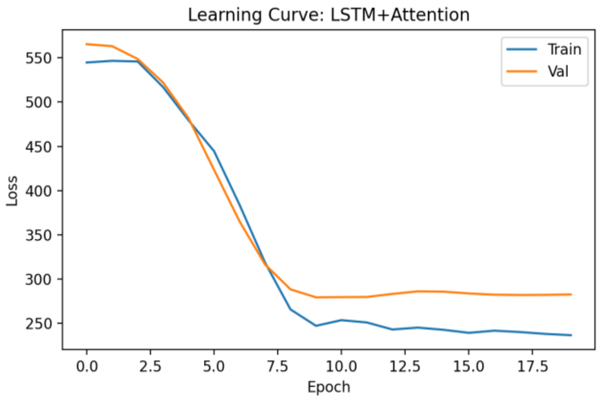

Figure 5. Learning curve of the LSTM model

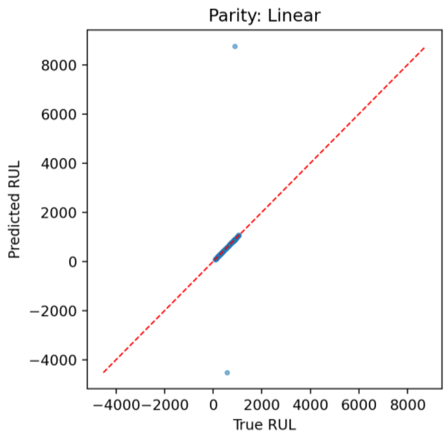

Figure 6. Parity plot of linear regression

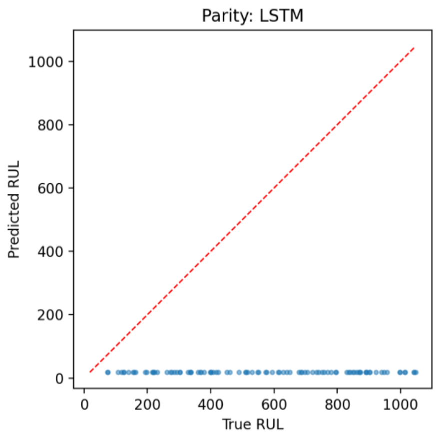

Figure 7. Parity plot of LSTM

Figure 8 illustrates the prediction performance of the LSTM with attention model, where the predicted RUL values remain nearly constant around 550. This behavior shows poor agreement between the predicted and actual RUL values, indicating that the model is unable to effectively capture the variations in battery degradation. As a result, the LSTM with Attention model demonstrates limited prediction accuracy and reduced overall performance. In contrast, Figure 9 shows that the RF model produces predicted RUL values that closely align with the actual RUL values. The strong agreement between the predicted and actual values demonstrates the high accuracy and reliability of the RF model. Therefore, the comparison between Figures 8 and 9 clearly indicates the superior performance of the Random Forest model for accurate battery RUL prediction.

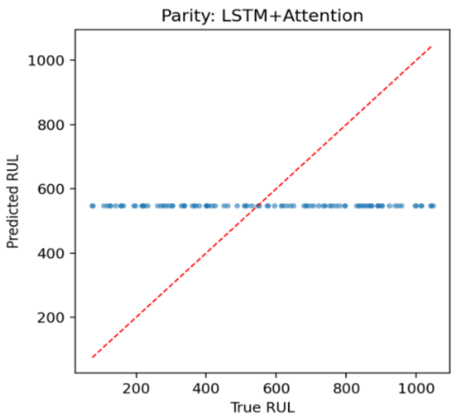

Figure 8. Parity plot of LSTM with attention

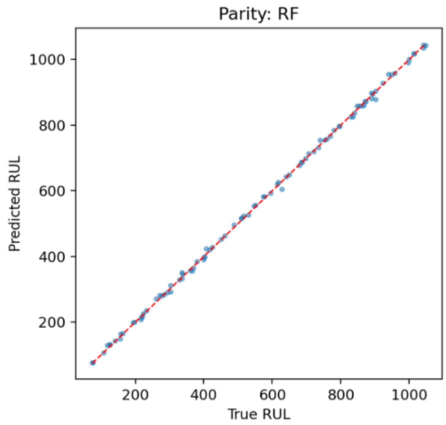

Figure 9. Parity plot of random forest

Figure 10 states that the residuals are predominantly concentrated around zero, indicating a good fit of the linear regression model with a few significant outliers. Figure 11 states that the LSTM residuals are widely distributed and predominantly negative, indicating systematic overestimation of the predicted RUL values and relatively poor model fit. Figure 12 states that the LSTM + attention residuals are distributed around zero with moderate spread, indicating improved prediction performance but some remaining errors. Figure 13 states that the RF residuals are closely centered around zero with a relatively narrow distribution, indicating high prediction accuracy and a good model fit. In addition, random forest offers lower computational requirements, faster training, and better interpretability, making it a practical choice for real-time RUL estimation in BMS applications [25].

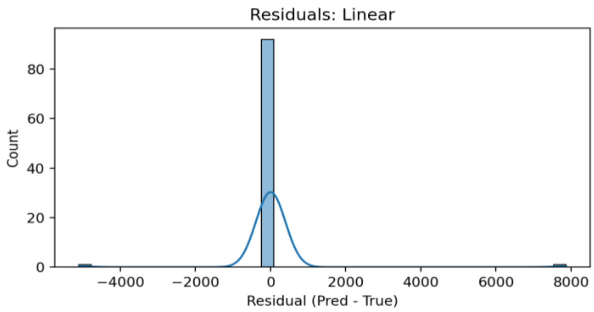

Figure 10. Residual analysis of linear regression

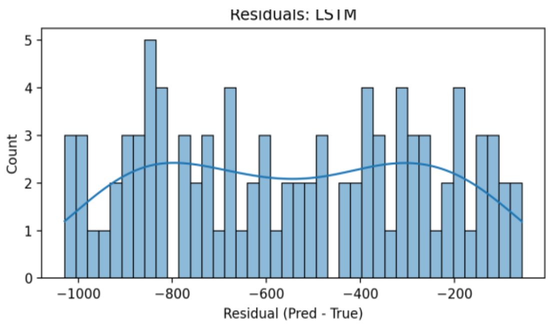

Figure 11. Residual analysis of LSTM

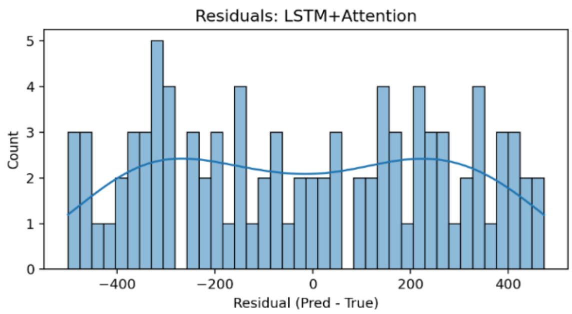

Figure 12. Residual analysis of LSTM with attention

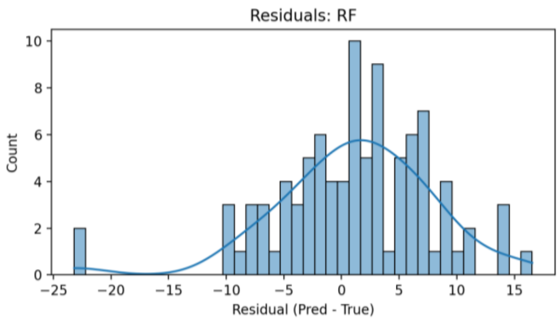

Figure 13. Residual analysis of random forest

4. CONCLUSION

This work investigated the prediction of the RUL of lithium-ion batteries using an ensemble learning framework based on the HNEI battery dataset. The performance of linear regression, random forest, LSTM, and LSTM with Attention models was assessed using the same training and testing conditions. Among the evaluated methods, the random forest model produced the best results, achieving an MAE of 5.20, RMSE of 6.83, MAPE of 1.33%, and an R^2 value of 0.997. These results indicate that the model effectively represents the nonlinear degradation behaviour of lithium-ion batteries while maintaining reliable prediction performance. Its low computational cost and straightforward interpretation make it a suitable candidate for BMS applications, including battery condition monitoring, predictive maintenance, and charging optimization. Since the present study was conducted using a laboratory-based dataset under offline conditions, additional validation using real-world electric vehicle battery data is required. Future research will focus on hybrid ensemble–deep learning approaches, explainable artificial intelligence (XAI) techniques for improved model transparency, and digital twin-enabled battery management for real-time diagnostics and decision support.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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M. Bhoopathi	✓		✓	✓	✓		✓			✓	✓		✓	✓
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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