

Predicting battery life performance using artificial intelligence techniques in electric vehicles

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ABSTRACT

Electric vehicles' (EVs) performance and sustainability are significantly influenced by the efficiency and lifespan of their lithium-ion batteries. This paper explores the critical factors affecting battery degradation, focusing on parameters such as charge cycles, thermal management, and voltage dynamics. Utilizing a dataset of 14 batteries, the study employs data-driven machine learning (ML) to predict the remaining useful life (RUL) of batteries. The ensemble-based regression model demonstrated superior predictive accuracy through comprehensive analysis, achieving R^2 values of 97.89% for training and 94.69% for testing. Feature importance analysis identified cycle index (CI) as the most critical determinant of battery health, followed by discharge time and voltage stability. Visualizations, including correlation heatmaps and residual plots, validate the robustness of the selected model. Additionally, sustainable charging strategies, such as steady current-steady voltage (also known as CC-CV), are highlighted for their role in enhancing battery longevity. This research offers actionable insights into battery management systems, providing a robust foundation for predictive maintenance and the development of sustainable electric mobility solutions.

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1. INTRODUCTION

Electric vehicles (EVs) are essential in the shift towards sustainable transportation, addressing global concerns about fossil fuel dependence and environmental harm [1], [2]. Among these batteries, electric vehicles (BEVs) are receiving the most attention due to their use of Li-ion batteries, extended lifespan, and efficiency [3], [4]. However, the performance and widespread adoption of EVs are heavily dependent on the reliability, lifespan, and cost of their batteries [5], [6]. Effective battery management is critical to achieving optimum potential and protection in EVs. The energy management system (EMS) regulates energy flow and generation, improving drivetrain efficiency [6]. Similarly, vehicle control units (VCUs) play a critical role in operational control by integrating safety mechanisms and managing auxiliary power supplies [7]. Despite these advancements, Li-ion batteries are prone to degradation due to factors like charge-discharge cycles, temperature fluctuations, and operational stress [8]. This degradation results in capacity fade and power loss, which presents challenges to the sustainability and economic viability of EVs [9], [10]. Recent advances in machine learning (ML) have revolutionized battery health monitoring and management. Techniques like regression models, ensemble learning, and artificial neural networks (ANN) provide precise predictions of key parameters such as the state of charge (SOC) along with the remaining

useful life (RUL) of batteries [11], [12]. Accurate RUL estimation enables predictive maintenance, reducing operational costs and enhancing battery performance [7], [13]. Additionally, sustainable charging methodologies like steady CC-CV can help reduce degradation and extend battery life [14], [15]. This paper investigates the use of data-driven ML to anticipate the RUL of Li-ion batteries, focusing on factors like charge cycles, discharge time, and voltage stability [16], [17]. By applying ensemble-based regression models, the study achieves high predictive accuracy, showcasing the potential of ML to optimize battery lifecycles. Feature importance analysis highlights the cycle index (CI) as the most significant factor in determining battery health, aligning with the natural aging process of Li-ion batteries [18], [19]. Visualizations, including correlation heatmaps and residual plots, confirm the robustness of the models and provide actionable insights for battery management systems. The findings from this research offer a comprehensive framework for predictive maintenance and lifecycle management in EVs, addressing the critical need for sustainability in electric mobility. By leveraging ML-driven insights, this study contributes to advancements in EV battery technology, paving the pathway for increasingly reliable and efficient electric transportation methods.

2. PROPOSED METHOD

The proposed method uses advanced data-driven machine learning techniques and simulation tools to predict the RUL of Li-ion batteries within EVs. The study starts by preparing a dataset that includes key battery parameters like CI, discharge time, and voltage profiles, which are derived from simulations designed to mimic real-world battery usage in EVs. Data preprocessing ensures the dataset's reliability by removing invalid entries [20], such as null or negative values. The input features are then standardized through normalization to keep things consistent, and the dataset is split into development (training) and evaluation (testing) stages as a ratio of 80:20 for model evaluation. A range of regression models is used to predict the RUL, with their performance assessed utilizing measures like mean absolute error (MAE) and R^2 [21], [22]. The ensemble-based technique proves to be the most effective, striking the right balance between high predictive accuracy and computational efficiency. This method performs exceptionally well, achieving R^2 values of 97.89% for training and 94.69% for testing. Feature importance analysis reveals that the CI is the most influential factor in battery degradation, followed by discharge time and voltage stability [23]. To validate the robustness of the selected model and ensure minimal bias and variance, the study uses visualizations such as correlation heatmaps, scatter plots comparing actual versus predicted RUL, and residual plots. The final model is integrated into EV battery management systems, enabling real-time monitoring of battery health and proactive maintenance. This integration offers valuable insights into battery conditions, optimizes usage patterns, and improves lifecycle management. By combining predictive analytics with advanced modelling [24], the proposed method promotes sustainable battery usage and boosts the overall performance and reliability of lithium-ion batteries in EVs.

2.1. Machine learning models

This study explores several regression models containing linear regression (LR), ridge regression (RR), lasso regression (Lasso), random forest (RF) regression, and ANN. Among these, RF regression proved to be the most effective for anticipating the RUL [25], achieving an impressive R^2 value of 97.89% during training.

2.1.1. MAE

K-nearest neighbor (KNN) regression stands out for having the lowest MAE values across both the model development and evaluation stages of the dataset. This highlights its potential to effectively learn the patterns in the statistics and generalize exceptionally well to new, unseen samples. While all the machine learning models show strong performance with comparable MAE values, KNN regression is particularly noteworthy for its ability to minimize error consistently [26]. Overall, the models demonstrate robustness in handling regression tasks effectively.

2.1.2. R^2 (R-squared)

The R^2 values for both the training and test datasets illustrate the models' effectiveness in explaining the variance in the dependent variable. All models perform well on the training dataset, showcasing their capability to record and represent the interrelations within the data [27]. On a test dataset, the models maintain high R^2 values, with KNN regression continuing to show a particularly strong performance [28]. This consistency between training and test results underscores the generalization capability of these models, indicating that they can effectively explain the variance in new, unseen data. Figure 1 shows the visualization that compares the performance of multiple regression models on two key metrics: MAE and R^2 for both training and test datasets.

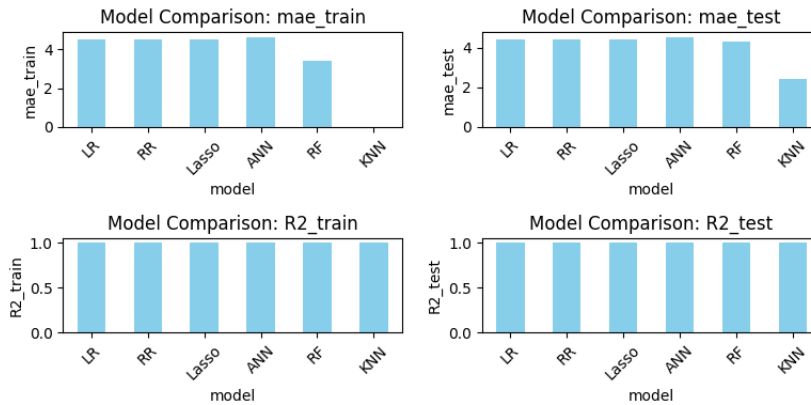


Figure 1. Visualization compares the performance of multiple regression models on two key metrics: MAE and R² for both training and test datasets

Table 1 compares various regression models used to predict battery life, evaluated based on MAE and R² (variance explained) [19], [20]. KNN regression achieves perfect metrics, though this may indicate overfitting. RF regression strikes a good balance, showing low error (mae_test = 4.301981) and high accuracy (R²_test = 0.999621), making it a robust model for predictions. Linear, Ridge, and Lasso regressions perform similarly [29], with consistent metrics across the board, while ANN regression displays the highest error, making it less suitable for this task. Overall, RF emerges as the most practical model for deployment, offering a good mix of accuracy and generalization.

Table 1. Comparison of regression models for battery life prediction

Model	MAE train	MAE test	R ² train	R ² test
Linear regression	4.548787	4.454378	0.999503	0.999547
Ridge regression	4.548623	4.454287	0.999503	0.999547
Lasso regression	4.548641	4.454329	0.999503	0.999547
Ann regression	4.659538	4.561503	0.999489	0.999531
Random forest regression	3.429135	4.301981	0.999750	0.999621
K neighbour regression	0.000000	2.413837	1.000000	0.999608

2.1.3. Random forest

The random distribution of residuals around zero, with no apparent pattern, indicates that the model is free from bias. While a few outliers with higher residuals point to occasional prediction errors, the overall variance is low [30], reinforcing the reliability of the RF model. Figure 2 depicts the actual and predicted RUL values by the residual plot.

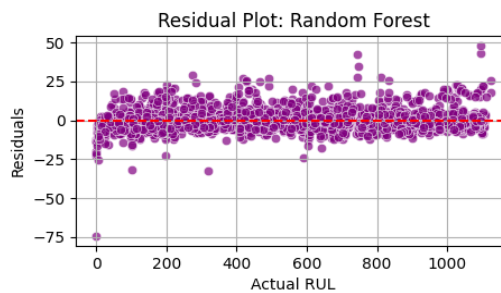


Figure 2. Actual and predicted RUL values by residual plot

Figure 3 is the learning curve for the RF model shown in the graph illustrating the relationship between the training set size and model performance, as measured by MAE. Initially, the training error (blue line) is relatively low at approximately 5 MAE, demonstrating that the model fits the training statistics well, even with smaller datasets, where the training set range grows, the training error decreases slightly and stabilizes, reflecting the model’s ability to learn effectively from larger datasets. Meanwhile, the validation error (orange colour line) starts at a higher value, around 10 MAE, suggesting overfitting when the dataset is

compact. However, as the training set range grows, the validation error uniformly declines, approaching training inaccuracy, and signaling improved generalization. The convergence of training and validation errors at a dataset size of approximately 10,000 samples shows that the model reaches a balance between bias and variance with enough data. This behavior highlights the scalability of the RF model, as it continues to benefit from additional training data while maintaining a low training error. The narrowing gap between the two errors further reinforces the reduced variance and enhanced generalization capability. These findings suggest that RF is a robust choice for tasks that require scalability and stable performance across both training and validation datasets. In summary, the model’s performance improves significantly with larger datasets, and 10,000 samples appear to be sufficient to minimize validation error while ensuring good generalization. This analysis emphasizes the importance of dataset size in optimizing model performance for machine learning tasks.

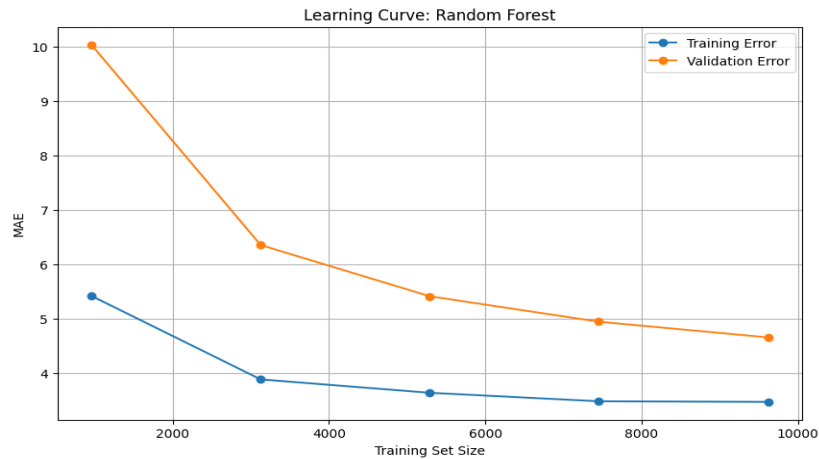


Figure 3. Learning curve analysis of RF model: training vs. validation error

3. RESULTS AND DISCUSSION

From Figure 4, the CI has a significant positive correlation with the minimum voltage charged (MinVC) (0.77) and a strong negative correlation with the maximum voltage discharged (MaxVD) (-0.79). This implies that as the CI increases, the minimum charge voltage rises, while the maximum discharge voltage sharply falls. This is crucial since variations in these voltages could indicate battery deterioration over time. The discharge time (s) (DT) has a strong positive correlation with both charging time (CT) (0.94) and time constant current (s) (0.91). This shows that as the discharge time increases, the charging time and time at constant current also grow. These factors are crucial because they show how well the battery manages time during operation. Decrement 3.6-3.4V (s) (D36-34) and time at 4.15V (T4.15V) (0.64) are in moderate relation with discharge time (s) (0.60). This suggests a steady loss of energy during battery operation, with the voltage decrement during discharge corresponding to longer discharge periods and time spent at certain voltages.

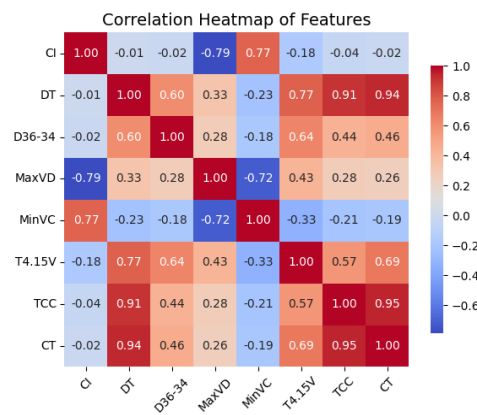


Figure 4. Correlation heatmap of features

The MaxVD has a significant negative correlation with the MinVC (-0.72). This shows an inverse relationship, where the maximum discharge voltage decreases as the minimum charging voltage increases, which is an important indicator for voltage dynamics in battery health. Time at 4.15V (s), charging time (s) (0.69), and time constant current (s) (0.57) show moderate associations. This implies that longer charging durations for batteries that require more time to achieve and maintain 4.15V may affect overall charging efficiency. Time steady current (s), as well as charging time (s), exhibit the strongest positive correlation (0.95), highlighting that the time spent at constant current during the charging phase directly relates to the overall charging time, a principal criterion for interpreting battery behavior.

From Figure 5, the RF model for forecasting the RUL of a battery identifies the CI as the dominant feature, highlighting that the number of charging cycles of charging is a critical component in battery deterioration. Other important contributors include discharge time, time at constant current, and time spent at 4.15V, which reflect the temporal and voltage-related aspects of battery performance. Features such as the maximum voltage during discharge and charging time were found to have a lesser impact, indicating they play a smaller role in predicting the RUL. This analysis ensures that the model is focused on the most relevant parameters for accurate predictions.

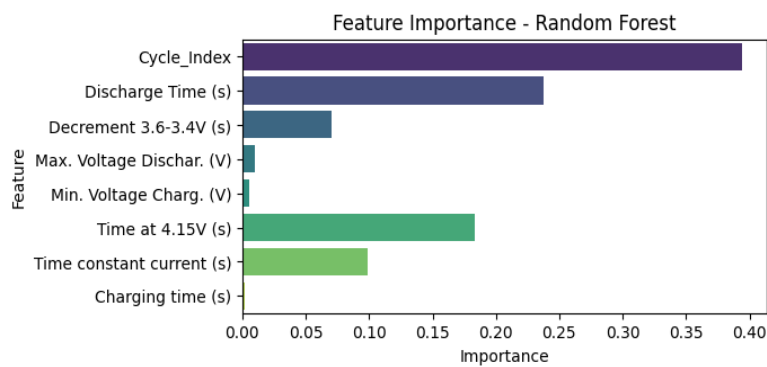


Figure 5. Shows the RUL of a battery

Figure 6 presents the overall visualization of the model’s performance, where Figure 6(a) clearly shows that the data points are closely aligned along the ideational fit line (red dashed line), illustrating the model’s exceptional accuracy in speculating the RUL of the battery. The minimal deviation observed between the forecast and actual values further highlights the reliability and robustness of the model, making it a dependable tool for real-time battery health monitoring and lifecycle management. This strong alignment implies that the model efficiently records the underlying patterns in the data, offering high predictive accuracy. In Figure 6(b), as the count of the cycle increases by a combination of charge and discharge, the RUL exhibits a consistent linear decrease, which is a typical reflection of the natural aging process of the battery. This linear relationship emphasizes the significance of the CI as the most influential feature in predicting battery degradation. The strong correlation between the CI and RUL further validates the model’s capacity to make accurate predictions based on this critical parameter, underscoring the importance of monitoring charge cycles to understand and anticipate battery performance over time.

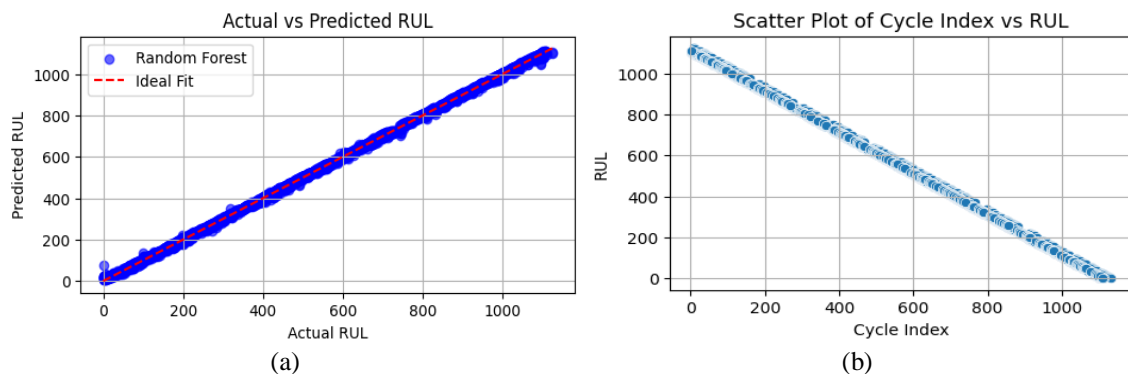


Figure 6. Performance analysis of the random forest model for battery RUL prediction: (a) Plot compares predicted and actual RUL values and (b) Demonstrates the inverse relationship between CI and RUL

4. CONCLUSIONS

This research presents a thorough inspection of the factors influencing the operation as well as the lifespan of Li-ion batteries in EVs. Through ML models, the paper highlights the critical role of charge cycles, thermal management, and voltage dynamics in battery degradation. Among the regression models evaluated, RF regression proved the most practical, balancing accuracy and generalization, with R^2 values of 97.89% (training) and 94.69% (testing). The results emphasize the importance of monitoring operational parameters like SOC and temperature to optimize battery life and enhance EV performance. This study lays the groundwork for predictive maintenance strategies and data-driven approaches in battery management.

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AUTHOR CONTRIBUTIONS STATEMENT

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Munavath Pavan Kalyan	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓	✓
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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : **O**riginal Draft

E : **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study are available from the corresponding author [SRS], on reasonable requests.





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