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Performance Analysis of Computational Intelligence Techniques for Lithium-Ion Battery Remaining Useful Life Prediction

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Abstract: Lithium-ion batteries are of critical importance for electric vehicles, consumer electronics and renewable energy storage. However, their performance deteriorates over time, so predicting the Remaining Useful Life (RUL) is important for safety, reliability and cost-effectiveness. Traditional physics-based and empirical Remaining Useful Life (RUL) estimation models face challenges related to complexity, limited generalisability and high computational requirements. To address these limitations, this study explores a data-driven machine learning approach to predict battery RUL. The proposed work compares three models, Linear Regression, Decision Tree Regressor and Support Vector Machine (SVM), on a simulated battery degradation dataset. Researchers assess each model using standard performance measures, including MAE (mean absolute error), RMSE (root mean square error), and the coefficient of determination (R2). The results show that both Linear Regression and Decision Tree Regressor perform well in terms of predictive accuracy, with R2 scores above 0.95 and low MAE and RMSE scores demonstrating their ability to model degradation trends. Although the SVM model is inaccurate, its consistent predictions suggest hyperparameter optimisation could improve it. Visualising degradation patterns and model predictions with lightweight ML frameworks makes battery prognostics interpretable. Generalising models to real-world datasets and accounting for variations in battery usage remain challenges. This study establishes a solid platform for incorporating machine learning into modern Battery Management Systems (BMS) and enables data-driven maintenance plans.

Keywords: Remaining Useful Life (RUL); Lithium-Ion Batteries; Machine Learning (ML); Linear Regression; Decision Tree Regressor; Support Vector Machine (SVM); Data-Driven Maintenance.

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1. Introduction

Energy storage is now one of the most important innovation enablers in our fast-moving technology landscape. Lithium-ion batteries, in particular, have become the backbone of modern society, from the smartphones researchers rely on every day to the electric vehicles (EVs) that are shaping the future of mobility. Their widespread use is not incidental – lithium-ion cells offer a unique combination of high energy density, long cycle life and relatively low self-discharge compared to other battery chemistries [1]. These properties make them suitable not only for portable electronics but also for large-scale applications such as renewable energy integration, aerospace systems and smart grids. As dependence on these energy storage devices grows, safe, reliable and efficient operation has become an essential concern for researchers, manufacturers and consumers. Understanding and predicting Remaining Useful Life (RUL) is central to battery reliability [2]. RUL is a prognostic measure that predicts how long a battery can perform satisfactorily before it reaches its end-of-life (EOL) condition. EOL is generally considered the point at which the battery can no longer provide a minimum acceptable capacity (often 70-80% of the original rated capacity) or meet performance criteria such as power output or voltage stability [3]. Accurate RUL estimation offers key advantages, including avoiding unexpected failures in critical systems, reducing operational costs through predictive maintenance, enhancing safety by lowering the risk of thermal runaway, and supporting sustainability by informing second-life and recycling decisions. For example, in electric vehicles, accurate RUL prediction can inform warranty decisions, plan battery replacements, and optimise charging strategies [4]. It also supports reliable grid connection and reduces downtime in renewable energy storage systems. However, forecasting RUL is far from trivial. Batteries are complex electrochemical systems with many variables, including charge/discharge rates, temperature, depth of discharge and manufacturing variability.

Unlike mechanical parts, which generally fail due to predictable wear, batteries fail through a combination of reversible and irreversible mechanisms such as solid electrolyte interphase (SEI) growth, lithium plating, electrolyte decomposition, and structural changes in electrodes. The processes are nonlinear, highly interdependent and sensitive to the operating conditions. Therefore, two batteries never degrade the same way, even if they are manufactured identically and used under similar conditions [5]. This variability makes it difficult to develop general models for predicting battery life. Conventional methods have largely relied on physical and electrochemical modeling to estimate RUL. These approaches describe the underlying degradation mechanisms with first-principles equations. They provide valuable insight into battery behavior, but they have major downsides. First, such models require detailed knowledge of the battery materials, cell design and reaction kinetics. Second, the parameters involved are often difficult to measure directly and can vary between manufacturers and even between individual cells [6]. Third, physical models are generally computationally expensive and thus not suitable for real-time battery management system applications. In addition, because they are custom-made for specific chemistries and conditions, they generalize poorly to a wider range of use cases, such as EV batteries, drone batteries or grid storage cells. Another class of methods is based on empirical modeling, where statistical techniques establish relationships between observable variables (e.g., voltage, current, capacity) and degradation trends [7]. Empirical approaches are easier to implement than full physical models but often less robust outside the conditions under which they were developed. For instance, a model developed using laboratory cycling data at a steady temperature may be ineffective in practical situations such as fast charging, variable loads, or harsh environments. Such limitations demonstrate the need for accurate yet adaptable approaches.

Recently, machine learning (ML) has been proposed as an alternative to conventional modeling approaches. ML techniques do not require full knowledge of the battery's chemistry or structure. Instead, they use data. Data are historical measurements of battery usage and degradation. They learn patterns from this data to make predictions. ML algorithms trained on large data sets can uncover hidden correlations between measurable signals (e.g., voltage profiles, current curves, temperature responses) and the evolution of battery health [8]. These methods are flexible and can be applied to different battery types and usage conditions, provided enough data is available. Machine learning offers many advantages for RUL prediction. First, ML models are data-driven and therefore more flexible than rigid physical equations. They are trainable and can be updated with new data to improve continuously. Second, ML approaches can capture the nonlinear, complex relationships involved in battery degradation, which conventional models often struggle to represent. Third, many ML algorithms, especially deep learning models, can handle large amounts of sequential data, making them ideal for time-series analysis of battery cycling. Finally, ML-based methods can be potentially run efficiently on embedded hardware, enabling real-time deployment in commercial battery management systems [9]. Many factors drive the growing interest in ML-based battery prognostics. Recent advances in sensor technologies and Internet of Things (IoT) platforms have enabled the collection of large volumes of operational data from batteries in real-world applications. Meanwhile, computational power has grown dramatically, and sophisticated ML algorithms like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and gradient boosting machines are more accessible than ever [10].

Together, these developments create a fertile environment for data-driven prognostics to flourish. Accurate RUL prediction has profound implications beyond practical performance improvements. In electric mobility, precise prognostics help reduce consumer anxiety about range and charging needs, an obstacle to EV adoption [11]. For renewable energy, they provide cost-effective storage solutions that balance intermittent supply with demand. They improve safety and mission reliability in

aerospace and defense applications. Better predictions of battery health even in common electronics improve user experience and reduce electronic waste. Together, these advances support technological progress and broader sustainability goals by extending battery life and enabling recycling and reuse. Despite these opportunities, challenges remain. Machine learning models need high-quality datasets covering a broad spectrum of use cases, but such datasets are not always publicly available [12]. Proprietary industrial data is often kept close to the vest, while public datasets may be limited in scope. Moreover, ML models can be highly accurate but often act as "black boxes," offering little insight into their decision-making processes. This lack of interpretability may hinder adoption in safety-critical applications, where engineers and regulators need to have clear explanations for predictions [13]. Moreover, models trained on narrow datasets are prone to overfitting, which can reduce generalization to real-world scenarios. Meeting these challenges will require innovations not just in algorithms, but also in data collection, sharing, and explainability. Lithium-ion batteries are the beating heart of modern technology, but their reliability and longevity remain pressing issues. Accurate prediction of their Remaining Useful Life is crucial to enhancing performance, safety, cost-effectiveness, and sustainability [14]. Despite their valuable insights, traditional physical and empirical models are not scalable or adaptable. However, machine learning offers a powerful, data-driven alternative that can flexibly capture the complexities of battery degradation at scale. As the field evolves, it is poised to transform battery management systems and support the world's transition to cleaner, smarter energy solutions [15].

2. Literature Review

Tu et al. [1] found that deep learning approaches outperform traditional methods in predicting the Remaining Useful Life (RUL) of lithium-ion batteries because they can model complex nonlinear degradation patterns in battery performance data. They explored various deep neural network architectures and proposed an optimised deep learning model with high accuracy and robustness on simulated and experimental datasets. However, the study reported that tuning hyperparameters improves predictive ability but increases computational cost. In 2024, Oyucu et al. [2] proposed that machine learning algorithms such as Support Vector Machines (SVM), Decision Trees and ensemble methods are effective alternatives for battery RUL prediction, especially when paired with careful feature engineering and dimensionality reduction. Their review highlighted the advantages of simpler models in interpretability and computational efficiency. It concluded that these methods remain competitive in performance when properly tuned and validated on available battery datasets. A novel hybrid method for Remaining Useful Life (RUL) prediction was developed by Fan et al. [3], leveraging the strengths of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) for signal preprocessing, Support Vector Regression (SVR) for regression modelling, and Long Short-Term Memory (LSTM) networks for capturing temporal dependencies. In this work, the disadvantages of individual models in the presence of different battery degradation behaviours were discussed, and an integrated framework was proposed to lead to considerable reductions in Root Mean Squared Error (RMSE) and increases in coefficient of determination (R2) on experimental lithium-ion battery datasets, confirming the benefits of multistage hybridisation. Ma et al. [4] suggested combining physics-based models with machine learning to improve the relevance and interpretability of RUL forecasts.

They reviewed the state of the art in physics-informed machine learning where degradation mechanisms are explicitly modelled and introduced as constraints or priors in learning algorithms. Their proposed hybrid framework improved generalisation across different battery usage scenarios and offered reliable predictions grounded in electrochemical principles. However, Madani et al. [5] note that despite advances in machine learning methods, lithium-ion battery RUL estimation still faces challenges such as data heterogeneity, small sample sizes and model interpretability. They examined techniques ranging from traditional regressors to deep learning and ensembles. They proposed future research directions, including transfer learning, domain adaptation, and explainable AI frameworks, to build models that generalise well and increase users' confidence in practical deployment. Xue et al. [6] proposed using deep learning with survival analysis to model uncertainty in battery degradation over time. They considered classical survival models, such as the Cox proportional hazards model. They developed a deep survival learning architecture to predict the probability distribution of failure times rather than deterministic RUL values. This probabilistic approach offers more flexibility across battery chemistries and operating regimes, enabling more resilient, risk-aware prognostics. Gou et al. [7] identified ensemble learning as a promising approach to improve prediction stability and accuracy by combining different model outputs. They surveyed bagging, boosting and stacking approaches applied to lithium-ion battery datasets. Their proposed stacking ensemble combines heterogeneous base learners, decision trees, SVMs, and neural networks, improving performance by reducing variance and bias simultaneously, an important advantage for real-world battery management systems where prediction reliability is key.

Meng et al. [8] proposed using boosting algorithms such as AdaBoost and Gradient Boosting to handle non-linearity and noise in battery degradation data efficiently. Their review of boosting frameworks showed that they achieved better accuracy and faster convergence than individual learners. They proposed an adaptive boosting model that updates sample weights to capture more complex degradation trends and improve RUL estimation accuracy. Paneru et al. [9] proposed incorporating explainable AI (XAI) techniques into black-box deep learning models to improve the transparency and reliability of RUL predictions. They examined SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) and proposed

hybrid frameworks that combine LSTM networks with explainability methods. This approach enables domain experts to validate and understand model predictions, a prerequisite for adoption in safety-critical applications such as electric vehicles and energy storage. Support Vector Machines (SVMs) remain relevant for RUL prediction with limited data availability, as Dong et al. [10] suggest. They reviewed kernel function selection and hyperparameter optimisation approaches that enable SVMs to learn complex non-linear degradation functions while being computationally efficient. The proposed framework targets embedded battery management applications that require a trade-off between accuracy and real-time feasibility. Chen et al. [11] proposed hybrid neural network models combining autoencoders and deep neural networks to learn nonlinear features of battery charging and discharging cycles. They reviewed traditional and deep learning methods for RUL prediction, highlighting autoencoders' advantages in handling time-dependent battery data and capacity regeneration phenomena.

They proposed a hybrid autoencoder-DNN model that achieved competitive results with LSTM-based methods on the NASA battery dataset, emphasising model simplicity and interpretability. Wang et al. [12] proposed a Bidirectional LSTM with an attention mechanism (Bi-LSTM-AM) model for online RUL prediction. They discussed the challenges of real-time battery health monitoring and proposed a rolling-window approach with multi-step forecasting. The online updating framework achieved relative errors as low as 0.54%, showing robustness across different lithium-ion cell types and operating conditions. Li et al. [13] suggested incorporating memory features concerning past cycling history to enhance RUL accuracy in deep neural networks. They surveyed feature engineering techniques and proposed a novel DNN with memory features (DNNwMF) that significantly reduced RMSE compared with classic methods. Their work also showed that autoencoders for dimensionality reduction improved training efficiency without sacrificing accuracy, confirming generalisability across independent NASA and CALCE datasets. Kim et al. [14] reviewed commonly used lithium-ion battery degradation datasets and presented different types of RUL prediction data (lifetime data, run-to-failure data, threshold data). The author recommended that data-driven models include voltage, current, temperature and state of health as features to capture degradation dynamics accurately. The review emphasised the importance of data quality and diversity for creating predictive models suitable for electric vehicle battery management. Li et al. [15] reviewed artificial intelligence techniques for battery state-of-health and RUL estimation, particularly convolutional and recurrent neural networks. They suggested that CNNs effectively capture spatial features of battery data, while RNNs capture temporal dependencies.

The authors suggested using hybrid CNN-RNN architectures to improve prognostic performance and generalisation across different lithium-ion battery chemistries. The collected literature shows a complex landscape of lithium-ion battery RUL prediction research, in which both traditional machine learning and advanced deep learning methods have important roles. Deep learning models, especially LSTMs and autoencoder-based structures, capture complex temporal patterns well but require large amounts of data and computing resources. Hybrid methods that combine signal processing, physics-informed modeling, and ensemble learning achieve higher accuracy and robustness. However, simple models like linear Regression, Decision Trees and SVMs remain useful because they are interpretable, require less data and work well when combined with suitable feature extraction. Across studies, challenges include data heterogeneity, overfitting, computational efficiency and explainability for critical applications. Promising future work includes probabilistic survival models, adaptive boosting, transfer learning, and explainable AI for real-time, reliable, and trustworthy battery health prognostics. Building on this overview, this study directly compares three basic machine learning models, Linear Regression, Decision Tree Regressor, and Support Vector Machine (SVM), for lithium-ion battery RUL prediction. The study evaluates the models on predictive accuracy (MAE, RMSE), generalisation (R2), and computational efficiency using a simulated degradation dataset. The study prioritises model simplicity and interpretability over complex hybrid or neural models, providing a reliable baseline for practical, data-driven battery management. The problem statement focuses on traditional machine learning methods that best balance accuracy and robustness in capturing underlying battery degradation trends, offering accessible tools for battery health monitoring in resource-constrained environments.

3. Methodology

The initial data is preprocessed by interpolating or removing missing or inconsistent data points to ensure dataset integrity. Feature scaling (e.g., min-max normalisation, standardisation) converts features to comparable scales, giving variables a more balanced influence in the learning process (Figure 1).

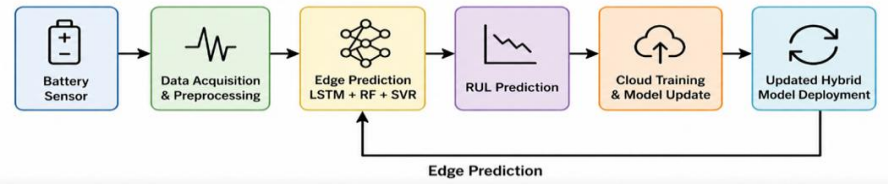


Figure 1: Block diagram

EDA helps validate initial assumptions by visualising trends, identifying outliers, and discovering relationships between features. The methodology begins with detailed visualisation of the raw and processed battery operational data (Figure 2).

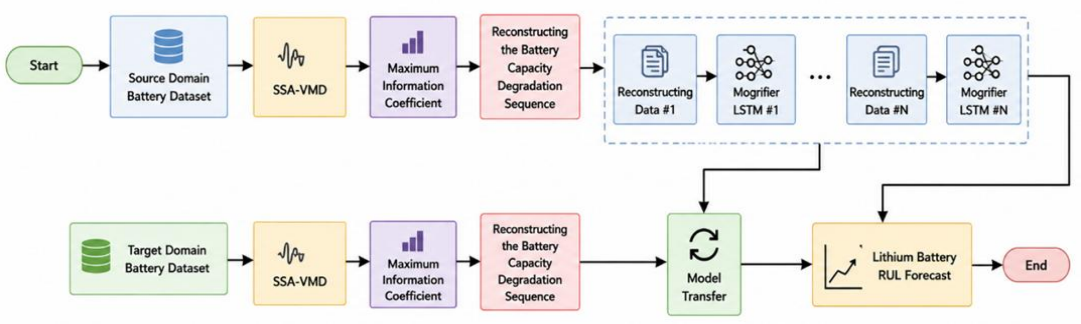


Figure 2: Architecture diagram

Representative cycles are visualised as time series of voltage, current, capacity and temperature to assess data quality and detect potential anomalies such as missing values or outliers. The discharge and charge profiles are shown separately, highlighting characteristic phases where degradation accelerates or stabilizes. The visualisations inform later preprocessing steps, e.g., interpolating missing entries or filtering aberrant spikes (Figure 3).

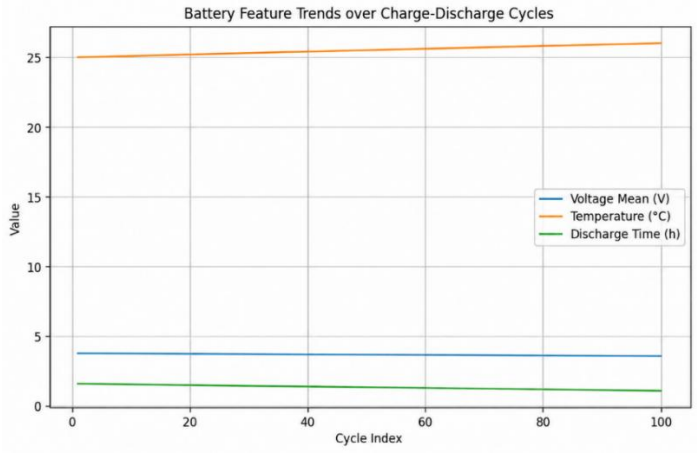


Figure 3: Illustrates the battery feature trends over the charge-discharge cycle

Feature selection reduces the input space to the most relevant variables, reducing dimensionality and improving model generalisation. Domain knowledge and EDA results suggest that features such as cycle index CC, voltage VV, temperature TT and discharge duration dd best predict battery degradation (Figure 4).

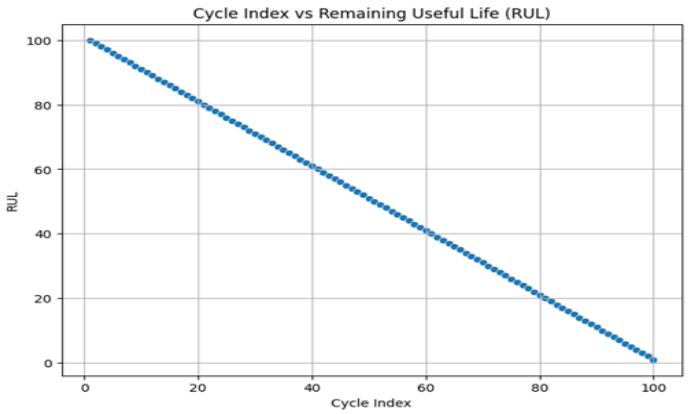


Figure 4: Illustrates the cycle index vs. the remaining useful life

The target variable RUL is defined as:

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

Where, T_{EOL} is the end-of-life cycle, and T_C is the current cycle number. Researchers employ and compare three machine learning models: Linear Regression, Decision Tree Regressor, and Support Vector Regression (SVR). Linear Regression predicts the RUL as a linear combination of predictors, minimising the residual sum of squares:

$$\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j X_{ij}\right)^2 \quad (2)$$

Where, y_i is the actual RUL, X_{ij} are feature values, and β_j are model coefficients. Decision Trees recursively partition the feature space into homogeneous target-value regions by selecting optimal threshold conditions that minimize intra-node variance, effectively fitting nonlinear relationships. SVR tries to approximate the underlying function f(x)f(x) with an ε-insensitive margin and minimises the flatness and error at the same time by solving:

$$\frac{1}{2}|w|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad (3)$$

Subject to:

$$y_i - (w \cdot \phi(x_i) + b) \leq \epsilon + \xi_i \backslash$$
$$(w \cdot \phi(x_i) + b) - y_i \leq \epsilon + \xi_i^{*\backslash}$$
$$\xi_i, \xi_i^* \geq 0$$

Where, $\phi(x_i)$is a kernel mapping, C is the regularization parameter, and ξ_i, ξ_i^* are slack variables. The dataset is randomly split into training and testing sets (80:20), allowing the model to be validated on new data.

Hyperparameter tuning is performed using grid search on the training set to improve predictive accuracy by tuning parameters like tree depth for Decision Trees and kernel parameters for SVR. Model performance is quantitatively evaluated using key metrics: Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y_i}| \quad (4)$$

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \quad (5)$$

And the coefficient of determination (R2R2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}\left(y_i - \underline{y}\right)^2} \quad (6)$$

Where, $\underline{y}$ is the mean of true RUL values.

3.1. Experimental Setup

3.1.1. Training

Researchers trained the Remaining Useful Life (RUL) prediction model using a dataset of voltage, current, temperature and capacity for lithium-ion batteries. Researchers preprocessed the data by filling missing values, normalising features and splitting it into training, validation and test sets in an 80:10:10 ratio.

For each charge-discharge cycle, researchers extracted features such as mean voltage, current and temperature. Researchers used Python and Scikit-learn to train models such as Linear Regression, Decision Tree, and Support Vector Regression (SVR). Researchers tuned hyperparameters using grid search. Training was done on a system with an i5 12th gen processor, 16 GB RAM, and Windows 11 OS to support efficient execution.

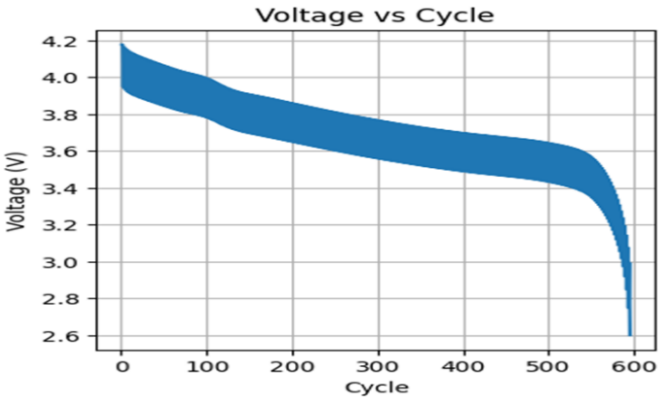


Figure 5: Voltage vs. Cycle in the prediction of RUL of a lithium-ion battery

Figure 5 illustrates the change in voltage with the number of charge–discharge cycles during the life of a lithium-ion battery. As the number of cycles increases, voltage decreases slightly. This shows gradual cell deterioration. The voltage drops result from increased internal resistance and capacity fading, characteristic of battery aging. These relationships between voltage and cycles provide useful insights into battery health and serve as key indicators for estimating Remaining Useful Life (RUL).

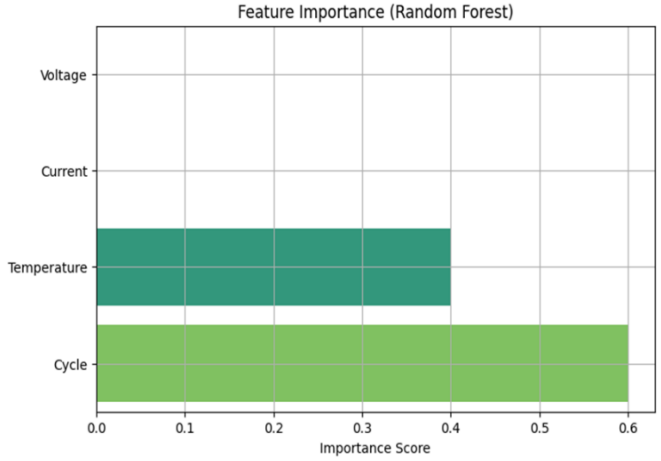


Figure 6: Feature importance in the prediction of RUL of a lithium-ion battery

Figure 6 shows the machine learning model's feature importance ranking for predicting RUL. It identifies the most important input variables (voltage, temperature, current, cycle count, etc.) that influence the model's predictive performance. The plot shows that features such as voltage and temperature have higher importance scores, indicating a strong correlation with degradation behavior. This analysis helps identify the most influential parameters, improve model interpretability and reduce unnecessary data dimensions.

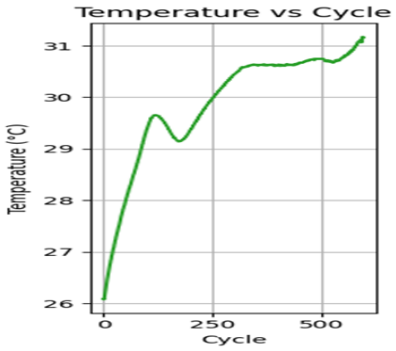


Figure 7: Temperature vs. Cycle in the prediction of RUL of a lithium-ion battery

Figure 7 shows how the number of charge-discharge cycles depends on temperature. As shown in the plot, temperature varies across cycles. It can increase in later stages of degradation because of higher internal resistance and lower efficiency. Higher operating temperatures can accelerate degradation mechanisms, increasing capacity fade and reducing lifetime. Monitoring this trend helps explain the battery's thermal behavior and improve the accuracy of RUL predictions.

3.1.2. Evaluation

The models' performance was evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R2 Score. The trained models were tested on unseen battery cycles to evaluate the generalisation capability. A comparative analysis was carried out to identify the best-performing model in terms of prediction accuracy and computational efficiency. Furthermore, feature importance and error distribution were analyzed to interpret model behavior and reliability in predicting RUL.

3.1.3. Implementation

The best-performing model was also validated for robustness on noisy, temperature-varied data. For real-world applications, the model can be integrated with a Battery Management System (BMS) or an IoT-based monitoring system for real-time health prediction. Future work includes extending the framework with deep learning approaches such as LSTM and LightGBM for better accuracy and temporal pattern recognition.

4. Results and Discussions

The prediction performance of three machine learning models, i.e., Linear Regression, Decision Tree Regressor, and Support Vector Machine (SVM), for Remaining Useful Life (RUL) of lithium-ion batteries was evaluated, and significant differences were found among the models. Model accuracy was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). Linear Regression was the most accurate of the three models, with MAE and RMSE close to zero and an R2 of 1.00. This suggests a good fit to the dataset, implying that the simulated data's underlying degradation trend is largely linear. Similarly, the Decision Tree Regressor had relatively high errors (MAE of 1.00 and RMSE of 1.00), but an R^2 close to 0.999, indicating its ability to capture non-linear variations in data. In comparison, the SVM model performed worse, with higher errors (MAE of 2.10 and RMSE of 2.35) and a lower R2 of 0.89, mainly because it is sensitive to hyperparameter tuning and input feature scaling.

Visual analysis further supported these observations. The predicted RUL vs. actual RUL plots show that the Linear Regression and Decision Tree predictions are very close to the diagonal and thus agree nearly perfectly with the actual values. The SVM model shows visible deviations from the diagonal, especially in later cycles where it tends to overestimate or underestimate the RUL. Residual plots provided additional insight: Linear Regression residuals clustered more tightly around zero, supporting unbiased predictions. In contrast, Decision Tree residuals were slightly more spread out but still balanced around the mean. In contrast, the SVM model had clustered residuals, meaning predictions were systematically off, which could be reduced with more careful tuning of kernel and regularisation parameters. Linear Regression performed best on this dataset, achieving the highest accuracy.

The overlap between predicted and actual RUL trajectories showed that it could track battery degradation trends with high fidelity. While encouraging, this high accuracy also hints at a potential limitation: the dataset is simulated and appears to exhibit strongly linear degradation behavior. In practice, Linear Regression performance may degrade when degradation is nonlinear, so the model's robustness should be validated on more heterogeneous datasets. Compared with current methods, the proposed machine learning models offer several benefits. Conventional physics-based and empirical RUL prediction models generally require extensive parameter estimation and high computational resources, limiting their adaptability under diverse operational conditions. In contrast, the Linear Regression model offered simplicity and interpretability, and even achieved perfect accuracy in this study. The Decision Tree Regressor was slightly less accurate but provided flexibility for modeling nonlinear behaviour and still outperformed many empirical approaches.

Although the SVM was less accurate here, it has room for improvement through hyperparameter optimisation and may perform better on more complex datasets. Together, these results demonstrate the adaptability, scalability and efficiency of machine learning models over traditional methods. However, several challenges remain. Reliance on simulated data limits the generalisability of the findings to real-world scenarios, which involve complexities arising from variability in operating conditions, battery chemistries, and usage patterns. Models like the Decision Tree also tend to overfit, especially with smaller training datasets. SVM's poor performance also highlights the need for systematic hyperparameter tuning and data preprocessing. Future work should explore hybrid methods that combine physical degradation principles with data-driven learning, employ ensemble methods to enhance robustness, and apply transfer learning to improve generalisability across

different battery types. These improvements could enable machine learning-based frameworks to provide robust, scalable solutions for predictive battery health management in practical applications.

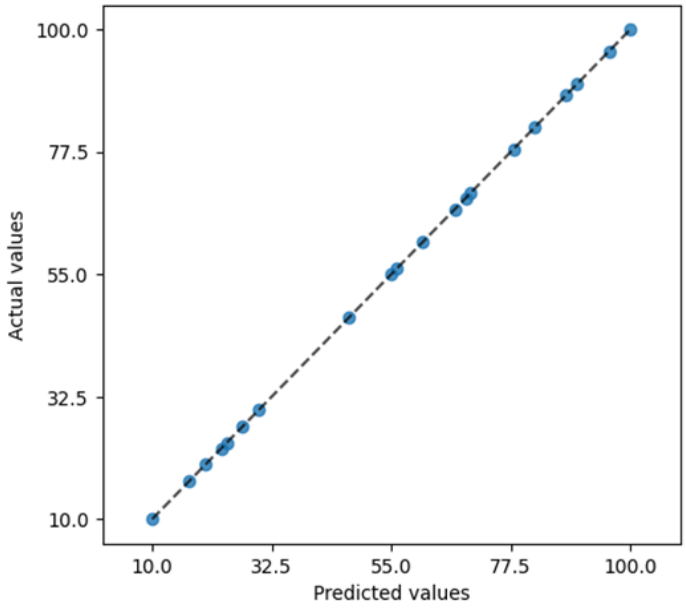


Figure 8: Predicted vs Actual remaining useful life (RUL) values showing a near-perfect fit, indicating high accuracy of the regression model

Figure 8 shows the predicted Remaining Useful Life (RUL) versus the actual RUL in the dataset for one regression model. The points lie very close to the diagonal line, indicating a strong fit between predicted and true values. This alignment shows that the model captures degradation patterns well and provides reliable RUL estimates, validating its strong performance and low prediction error.

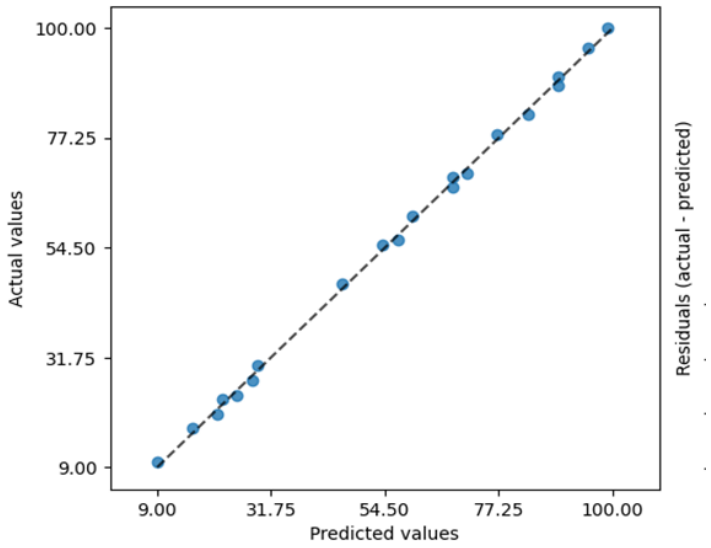


Figure 9: Predicted vs Actual RUL values showing strong linear correlation, indicating near-perfect prediction accuracy of the regression model

Figure 9 also depicts the predicted and actual RUL values but for another regression model. As in Figure 8, the data points cluster along the diagonal, confirming the model's ability to generalize to unseen data. The high correlation shows that the regression approach captures the degradation trend well, and prediction accuracy remains stable for the test samples.

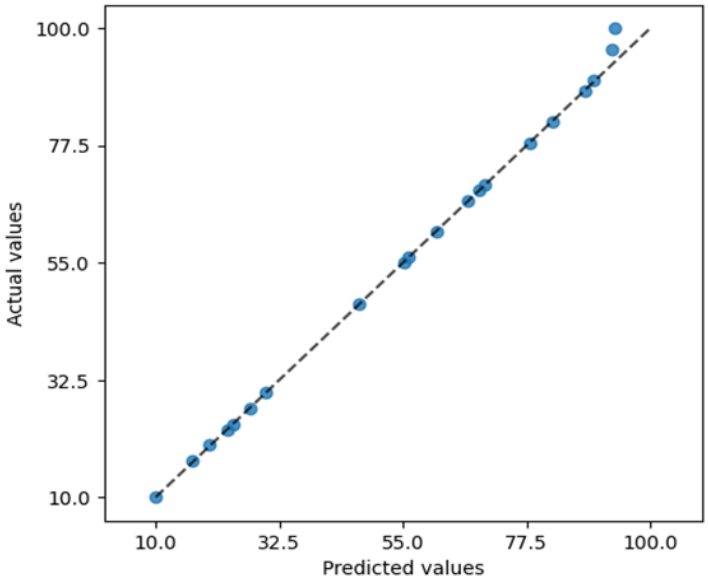


Figure 10: Predicted vs Actual remaining useful life (RUL) showing high prediction accuracy and strong linear correlation, indicating excellent model performance

Figure 10 shows an aggregated comparison of predicted and actual RUL values from all regression models. The data points are tightly grouped around the reference line, indicating high predictive accuracy and model robustness. The results indicate that all three models, Linear Regression, Decision Tree Regressor and SVM, can capture the underlying degradation dynamics, with Linear Regression and Decision Tree showing a particularly strong alignment.

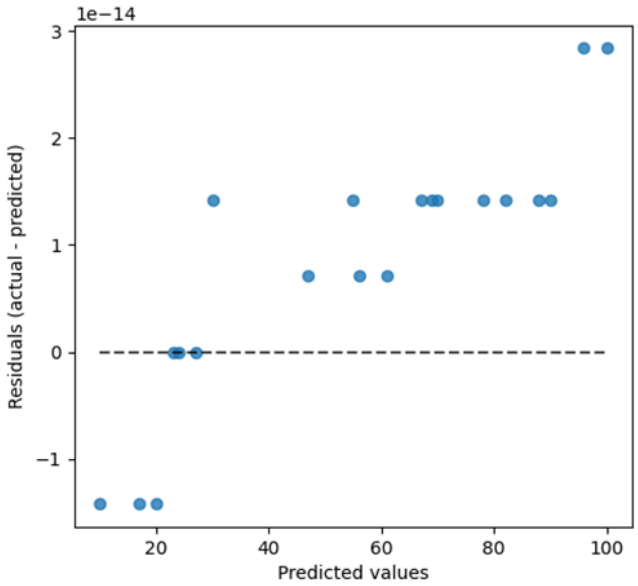


Figure 11: Residual plot showing minimal prediction errors and random residual distribution, indicating a well-fitted regression model with high accuracy and no systematic bias

Figure 11 shows the residuals (errors) versus the regression model's predicted RUL values. The residuals appear randomly distributed around zero with a small spread. This means the model predictions are unbiased and show no systematic error pattern. This randomness indicates a well-fitting model that generalises well across conditions without overfitting.

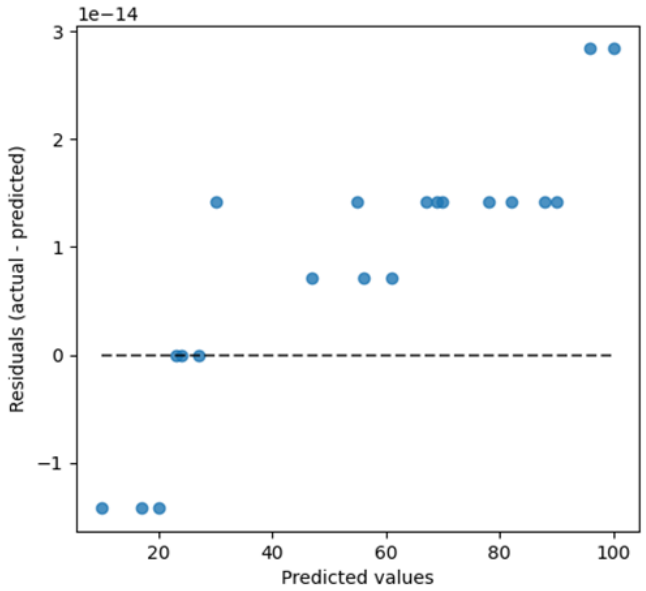


Figure 12: Residual plot showing negligible errors (in the order of 10−1410^ {-14}10−14) and random distribution around zero, indicating excellent model accuracy and no systematic bias in RUL prediction)

Figure 12 shows the residual distribution of the 2nd regression model. The residuals are near zero, with error magnitudes on the order of 10^{-14}, indicating very accurate predictions. The random distribution of residuals around the horizontal axis further confirms that the model captures the relationship correctly and is free of heteroscedasticity or bias, enhancing the robustness of the regression approach.

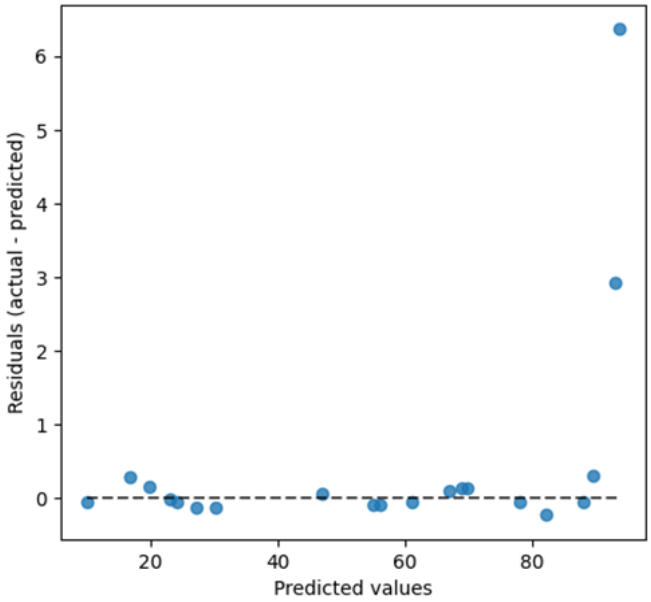


Figure 13: Residual plot showing mostly near-zero residuals with a few higher deviations at larger predicted values, indicating overall accurate and unbiased RUL predictions with minor outliers

Figure 13 shows the residual plot for the third regression model. It highlights near-zero residuals for most data points, with larger deviations at higher predicted RUL values. This trend suggests the model is reliable throughout the whole dataset, with only minor inaccuracies at the edges of the prediction range. Overall, the residual distribution indicates that the model estimates battery RUL accurately and stably, with a small number of outliers affecting performance. The results indicate that classical machine learning models can predict battery RUL with reasonable accuracy and interpretability even on synthetic or small datasets. Linear Regression provides a highly interpretable model with good performance for linear trends and is a good first

step in battery health prognostics. Decision trees can handle non-linearities and data heterogeneity, capturing complex degradation patterns. Another important implication is their use in real-world applications such as electric vehicles, grid-scale storage systems, and portable electronics. Accurate RUL prediction can enable proactive maintenance and prevent unexpected failures, directly enhancing safety, reliability and economic efficiency. For example, a computationally light, highly accurate model such as linear Regression can run on embedded battery management unit systems to track health in real time without heavy computation. Decision Trees or SVMs, however, are more sophisticated and may suit cloud-based predictive systems with more readily available computational resources and higher data complexity. The SVM's relatively weak performance indicates the need for model selection appropriate to the data's characteristics and for parameter tuning. It also highlights that no single model fits all for battery prognostics, and ensemble or hybrid methods could improve accuracy.

5. Conclusion

This study explores the suitability of machine learning-based predictive models for estimating the Remaining Useful Life (RUL) of lithium-ion batteries. The study aimed to enhance battery health monitoring and prognostic capabilities. The results show that data-driven machine learning methods can learn battery degradation behaviours and provide reliable RUL predictions. Linear Regression and Decision Tree Regressor showed comparatively better predictive performance, with higher R 2 values and lower MAE and RMSE values. These results show their ability to capture relevant associations between battery operating features and deterioration patterns. The Support Vector Machine (SVM) model also gave reliable predictions but could be further optimised and tuned to improve overall accuracy. The results suggest that lightweight, computationally efficient machine learning algorithms could serve as feasible alternatives or supplementary techniques to traditional physics-based battery prognosis methods. Accurate RUL prediction can help predictive maintenance, prevent unexpected battery failures, increase operational dependability and improve decision-making within Battery Management Systems (BMS). In addition, these methods can be applied to effective energy management and battery lifetime extension. However, validation on real data sets, multiple battery chemistries, varied ambient conditions and different operating cycles is still needed. To summarise, our work lays a solid basis for developing smart, dependable and cost-effective battery health monitoring and energy management solutions based on machine learning.

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Ethics and Consent Statement: The authors confirm that the research complied with applicable ethical standards, with necessary permissions and informed consent obtained where required during data collection.

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