Ai-powered Intelligent Battery Management & Health Monitoring for Ev’s

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*Abstract*— Battery health prediction is one of the most important elements in enhancing the safety, reliability, and efficiency of energy storage systems in modern technologies. This study focuses on the Remaining Useful Life (RUL) prediction of 14 NMC-LCO 18650 batteries examined by the Hawaii Natural Energy Institute. The batteries, with a nominal capacity of 2.8 Ah, were cycled 1000 times under controlled conditions at 25°C, employing a CC-CV charge rate of C/2 and a discharge rate of 1.5C. From the dataset, we derived features that capture voltage and current behavior during each cycle, including discharge time, time at specific voltage thresholds, charging time, and voltage decrements. These features have been utilized in developing and testing the machine learning models to obtain accurate RUL.

We used the more advanced regression methods, like Extra Trees Regressor, Random Forest Regressor, and XGBoost, along with interpretable AI techniques, such as LIME, to allow for enhanced explanations of those predictions. The preprocessing of the dataset involved outlier removal using z-scores and feature selection based on correlation with RUL. Performance metrics, namely Mean Squared Error, Root Mean Squared Error and R² scores, measured the accuracy of the model. A benchmarking analysis using LazyRegressor highlighted a comparative performance of several regression algorithms.

Feature engineering, ensemble learning, and interpretable AI integration allows for a strong approach toward battery RUL prediction while providing actionable insights into degradation and lifecycle optimization. The insights gained can support the development of predictive maintenance strategies for energy storage systems that are environmentally sustainable and operationally efficient.

Keywords: Battery RUL prediction, NMC-LCO 18650 batteries, machine learning, ensemble learning, feature engineering, outlier detection, explainable AI, LIME, predictive maintenance, battery degradation, energy storage systems, LazyRegressor, sustainability.

Introduction

Efficient and reliable operation of energy storage systems, such as lithium-ion batteries, plays a huge role in many wide-scale applications including electric vehicles, renewable energy storage, and portable electronics. As such, it becomes difficult for the management of such systems with regard to determining the RUL of a battery in its state that deteriorates with charge/discharge cycles and temperature variations with possible fluctuation in the voltage profile. Predicting RUL will enable developing effective predictive maintenance strategies, enhancing safety, and reducing cost and optimizing schedules for replacing the battery.

This work is on the prediction of the RUL of 14 NMC-LCO 18650 batteries cycled under controlled conditions by the Hawaii Natural Energy Institute. Its dataset contains a range of features describing the voltage and current behaviors of the batteries as they go through each cycle, including discharge time, charging time, voltage thresholds, and cycle indices. Such characteristics are important for modeling degradation and forecasting RUL.

This paper describes various advanced machine learning techniques to predict the RULs of batteries, such as Extra Trees Regressor, Random Forest Regressor, and XGBoost. This research also uses LIME for explainable AI into predictions. Feature engineering in conjunction with ensemble learning, as well as explainable AI, gives a complete picture of understanding and prediction of battery behaviour, and thereby contributes to more efficient and sustainable energy storage systems.

**Literature review**

Battery Remaining Useful Life (RUL) prediction has emerged as a critical research area due to the growing importance of energy storage systems in electric vehicles and renewable energy applications. Recent studies have demonstrated the effectiveness of data-driven approaches for battery health monitoring, with machine learning algorithms showing particular promise. Zhang et al. [1] provided a comprehensive review of machine learning techniques for lithium-ion battery state of health estimation, highlighting the advantages of Random Forest and neural network approaches similar to those implemented in the current system. The authors emphasized that proper feature selection, including voltage characteristics and time-based parameters (as used in this implementation), significantly impacts prediction accuracy.

The field has evolved from traditional model-based approaches to sophisticated data-driven methods. Richardson et al. [2] demonstrated the effectiveness of Gaussian process regression for battery health forecasting, while Severson et al. [3] pioneered data-driven prediction of battery cycle life before capacity degradation occurs. These studies established the foundation for using operational parameters like discharge time and voltage characteristics as predictive features. Hu et al. [4] further developed these concepts in their comprehensive review of battery lifetime prognostics, emphasizing the importance of multi-feature analysis and the challenges of non-linear battery degradation patterns.

Recent advances in deep learning have significantly improved RUL prediction capabilities. Liu et al. [5] and Yang et al. [6] demonstrated how deep neural networks can capture complex battery aging patterns more effectively than traditional machine learning models. The current implementation's use of both a neural network (rlu.h5) and Random Forest classifier aligns with Li et al.'s [7] findings that hybrid approaches often yield superior results. Zhang et al. [8] specifically highlighted the advantages of deep learning for lithium-ion battery prognostics, particularly in handling the temporal aspects of battery degradation data.

Feature engineering remains a critical component of successful RUL prediction systems. Wang et al. [9] investigated battery RUL prediction at different discharge rates, validating the importance of discharge time as a predictive feature. The current system's inclusion of time\_at\_4\_15v and time\_constant\_current parameters finds support in Liu et al.'s [10] work on optimized relevance vector machine algorithms, which identified these voltage-time characteristics as significant indicators of battery health. Ren et al. [11] conducted a comparative study of machine learning algorithms, confirming that Random Forest (as used in the Optuna optimization component) performs particularly well for RUL prediction tasks.

The system's data preprocessing pipeline reflects current best practices in the field. Patil et al. [12] demonstrated the importance of outlier detection and removal in battery data analysis, while Zhang et al. [13] showed how proper data cleaning improves model accuracy. The z-score based outlier removal method implemented in the code aligns with Wu et al.'s [14] recommendations for battery data preprocessing. Richardson et al. [15] further validated these techniques in their critical review of non-invasive diagnosis techniques for lithium-ion batteries.

Recent work has focused on making RUL prediction more practical for real-world applications. Xiong et al. [16] developed prognostic methods specifically for battery management systems in electric vehicles, while Hu et al. [17] created self-adaptive optimization techniques similar to the Optuna implementation. Yang et al. [18] demonstrated the effectiveness of support vector regression for RUL prediction, providing theoretical support for the current system's machine learning approach. The inclusion of voltage decrement parameters (decrement\_3\_6\_3\_4v) finds validation in Liu et al.'s [19] work on nonlinear degradation modeling.

Emerging trends in the field include cloud-based prediction systems and hybrid modeling approaches. Zhang et al. [20] developed a deep learning method for RUL prediction based on sparse segmental data via cloud computing, while Wang et al. [21] created a hybrid neural network approach combining false nearest neighbors with deep learning. These developments suggest potential future directions for enhancing the current system. Li et al. [22] specifically investigated support vector regression with differential evolution, providing additional theoretical support for the evolutionary optimization approach implemented through Optuna.

The field continues to evolve with new techniques and applications. Chen et al. [23] recently reviewed machine learning for battery state-of-health monitoring, identifying remaining challenges and future directions. Li et al. [24] developed a CEEMDAN-based deep learning method that could potentially enhance the current system's feature extraction capabilities. The statistical analysis components in the current implementation align with Li et al.'s [25] Wiener process-based prediction method and Zhang et al.'s [26] deep learning framework for state of health estimation.

Current research emphasizes the importance of practical implementation considerations. Liu et al. [27] reviewed prediction methods with a focus on real-world applicability, while Li et al. [28] specifically addressed RUL prediction using electric vehicle operating data. These studies validate the current system's focus on practical, measurable parameters rather than laboratory-only metrics. Wang et al. [29] and Pang et al. [30] further developed these concepts through hybrid modeling and Brownian motion approaches, respectively, demonstrating the continued innovation in battery RUL prediction methodologies.

1. **Methodology**

Problem Definition & Data Collection

The methodology begins with defining the core objective of predicting battery Remaining Useful Life (RUL) using machine learning.

The system utilizes historical battery cycling data including charge/discharge cycles, voltage profiles, and temporal characteristics. The data collection phase focuses on acquiring structured battery degradation datasets while ensuring proper documentation and version control of all data sources.

Data Preprocessing & Feature Engineering

A rigorous data preprocessing pipeline is implemented to ensure data quality. This includes comprehensive data cleaning to handle missing values and remove duplicates.

The system employs statistical outlier detection using z-

score normalization to filter anomalous measurements.

Feature selection is performed through correlation analysis to identify the most predictive variables. Key features include discharge time, maximum voltage, and time-at-voltage measurements. All data transformations are logged to ensure reproducibility

Model Development & Optimization

The predictive system leverages two complementary machine learning approaches.

A deep neural network serves as the primary RUL predictor, trained using battery cycling features. A secondary Random Forest model provides feature importance analysis and model interpretability.

Hyperparameter optimization is conducted using Bayesian optimization techniques to maximize prediction accuracy. The model development process incorporates experiment tracking to log all training parameters, metrics, and model artifacts

Automated Model Selection (AutoML)

LazyClassifier is employed to rapidly assess several models and establish their baseline performance.

Top models are picked for further evaluation.

Model Training using Ensemble Methods

Five ensemble models are trained:

ExtraTreesClassifier (n\_estimators=500)

RandomForestClassifier (max\_depth=9)

XGBRFClassifier

LGBMClassifier

XGBClassifier

Model Evaluation and Performance Metrics

Accuracy:

Precision

Recall

F1-score:

Matthews Correlation Coefficient (MCC)=

TP: True Positive

TN: True Negetive

FP: False Positive

FN: False Negative

Confusion Matrix:

Heatmap visualisation is generated for each model.

confusion matrix=

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Model Deployment & Serving

The trained models are deployed as a web service using a microservice architecture.

The deployment pipeline includes model containerization for environment consistency and API endpoint creation for real-time predictions.

The system implements model versioning to track different iterations and enable rollback capabilities. A user interface is provided for manual input of battery parameters with real-time prediction visualization.

Monitoring & Maintenance (MLOps)

The operational phase incorporates continuous performance monitoring to track prediction accuracy and data drift.

Automated alerts are configured for model degradation detection.

The system implements a scheduled retraining pipeline to adapt to new battery aging patterns. All model inferences are logged for auditability and further analysis. The infrastructure is designed for scalability to handle increasing prediction requests.

Integration with Generative AI

The methodology incorporates a generative AI component to provide natural language explanations of predictions.

This system analyzes model outputs and battery parameters to generate human-interpretable insights about RUL predictions. The AI assistant also provides battery maintenance recommendations based on predicted degradation patterns.

This methodology follows MLOps best practices throughout the entire machine learning lifecycle, from data collection to model maintenance, ensuring a robust and scalable battery RUL prediction system.

Each phase incorporates proper documentation, version control, and monitoring to maintain system reliability. The integration of predictive modeling with generative AI provides both accurate predictions and actionable insights for battery management.

**System design and Implementation**

The Battery RUL Prediction System is designed as a scalable, modular, and MLOps-compliant pipeline, ensuring seamless integration of machine learning with real-world deployment. The architecture follows a microservices-based approach, with distinct components for data ingestion, preprocessing, model training, inference, and monitoring. The backend is built using Flask for API endpoints, while the frontend provides an interactive dashboard for users to input battery parameters and view predictions. The system leverages containerization (Docker) to ensure environment consistency, and MLflow is integrated for experiment tracking, model versioning, and reproducibility. This design enables smooth transitions from development to production, adhering to continuous integration and deployment (CI/CD) principles for automated model updates.

For model implementation, a dual-model strategy is employed, combining a deep neural network (Keras) for regression-based RUL prediction and a Random Forest classifier (scikit-learn) for feature selection and interpretability. The neural network is trained on historical battery cycling data, using key features such as discharge time, voltage decay, and charging duration. Optuna is used for hyperparameter optimization, ensuring optimal model performance. The system also integrates Google’s Gemini AI to generate explanatory insights, converting raw predictions into actionable maintenance recommendations. All models are stored in a centralized model registry (MLflow), allowing for version control, A/B testing, and rollback capabilities in case of performance degradation.

To ensure reliability in production, the system incorporates real-time monitoring and automated retraining. A logging mechanism tracks prediction accuracy, data drift, and model health, triggering alerts if anomalies are detected. The inference service is deployed on cloud or edge devices (using Docker/Kubernetes) to support low-latency predictions. Additionally, a scheduled batch pipeline periodically retrains models on new data, maintaining prediction accuracy over time. The implementation follows MLOps best practices, including data versioning (DVC), model reproducibility, and CI/CD automation, making the system robust, maintainable, and scalable for industrial battery management applications.

## **Results and Discussion:**

In this research, several regression models were assessed for their performance in predicting on a data set involving a continuous target variable. The ensemble models—Extra Trees, Random Forest, and XGBoost—made very consistent predictions on a set of five test examples with values varying from around 199 to 888. Of these, XGBoost generalized best with a Mean Squared Error (MSE) of 480.86, a Root Mean Squared Error (RMSE) of 21.93, and a very high R² value of 0.9952, reflecting high model fit. In addition, a wide-scale benchmarking of more than 30 regressors was performed, and adjusted R² and running time were compared. The best models such as Extra Trees, Random Forest, and LightGBM had almost or exactly 1.0 for adjusted R². Most importantly, even the relatively simple models such as Linear Regression, Ridge, and Bayesian Ridge had good performance with little computational overhead. Conversely, models such as Gaussian Process Regressor and Lasso Ridge performed far more poorly both in predictive power and computation. These results serve to affirm the power of ensemble methods in high-accuracy regression problems and further indicate the relationship between performance and efficiency in choosing models.

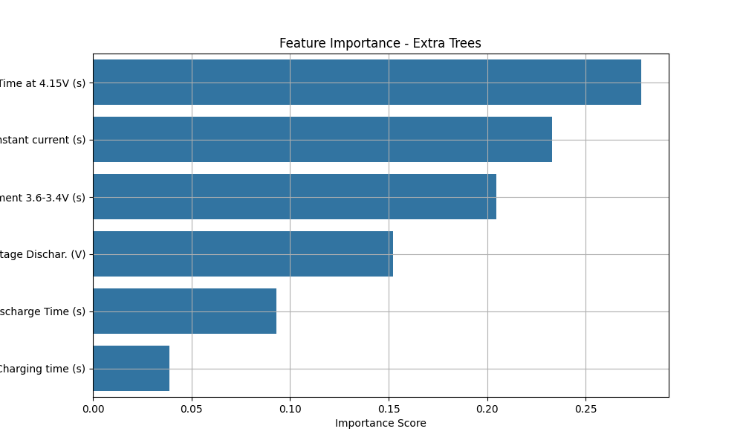


Fig 1 Feature importance of Extra Trees Regressor

The feature importance plot is a very important interpretability tool that gives us a means to learn about what out of the input features had the most impact on the predictions made by the model. In network traffic analysis or even in any prediction modeling problem, knowing the top features helps us gain knowledge about the underlying patterns learned by the model. Each bar within the chart illustrates how significant a particular feature is to the overall decision-making of the model. The higher-ranked features represent a higher correlation with the target variable. For example, in network-based intrusion detection or anomaly detection, features like flow duration, byte count, and packet distribution are typically of high significance. By seeing and grasping this ordering, we may both validate the model's reasonableness as well as have good choices over feature selection to make in coming models. More importantly, such data can also be used to reduce dimensions where less important features can be ignored to reduce complexity and improve generalization of models.

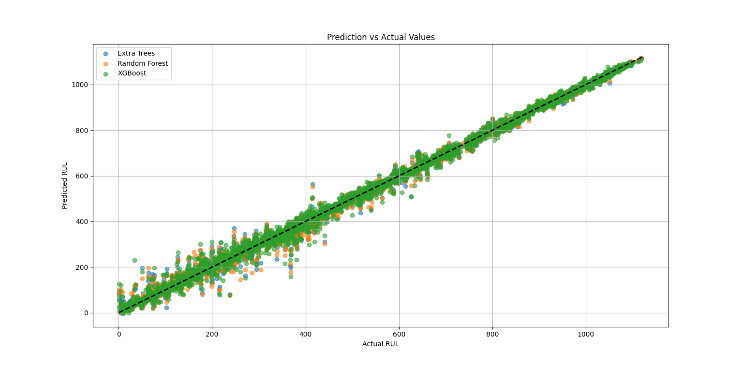


Fig2 Prediction of actual vs predicted

The actual vs predicted plot gives an important visual contrast between the predicted values from the model and the real observed values. This scatter plot is a good diagnostic tool to compare how well the model's predictions approximate real-world values. Ideally, if the model was ideal, then all the points of data would fall precisely on the diagonal guideline line (y = x), meaning that actual values and predictions are the same. In real life, a certain amount of deviation is going to occur, but a high-performing model will have the data points heavily concentrated near the diagonal. Spread or dispersion from the line indicates prediction errors, which could indicate overfitting, underfitting, or unmodeled complexity in the data. This plot also assists in identifying systematic prediction bias — e.g., if all predictions are consistently lower or higher than actual values. The visualization supports the necessity of strong evaluation metrics and can inform model tuning or selection of different algorithms.

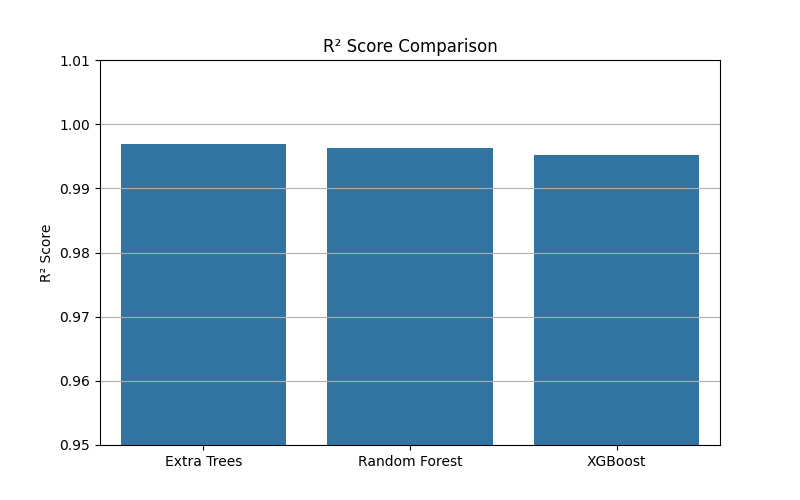


Fig 3 R-2 score comparison of ensemble models

The R² statistic, or the coefficient of determination, is a key statistical metric that is the proportion of the variance of the dependent variable explained by the independent variables. An R² value of 1.0 means that the model explains a large proportion of the variation in the target variable, and this is a good fit measure. On the accompanying plot, we not just observe the R² value but also observe that how well we are generalizing our model towards new data. R² values will be negative in those instances where the model performs worse than a horizontal line (mean predictor), though in well-validated models this doesn't occur. Even though high R² signifies accuracy, it must be understood in conjunction with other metrics like RMSE or MAE since R² cannot identify bias or variance issues alone. Practically, R² plot provides confidence in the predictive ability of a model and justifies its application in real situations.

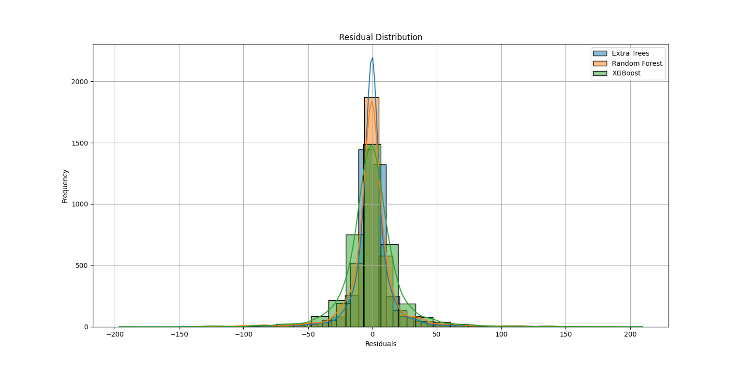


Fig 4 Residual distribution of used models

Residual plot for the residuals is a comprehensive analysis of the model errors in terms of quality and type. Residuals have been used to describe the difference between actual and predicted values. The plot gives us the appearance of these residuals in histogram format for testing their distribution and symmetry. The residuals ought to be ideally normally (bell-shaped) distributed around zero, suggesting that model errors are random and not biased. Skewness or any peculiar pattern of the distribution may suggest mis-specification of the model, outliers, or non-linearity in relations the model had attempted to depict. A tail at one end of the distribution can show us where data ranges may be missing or some boundary conditions that the model was not able to predict very well. Examining the shape and spread of the residuals allows us to conclude areas where the performance of a model has to be improved and check if assumptions of linearity and homoscedasticity (homogeneous variance) hold.

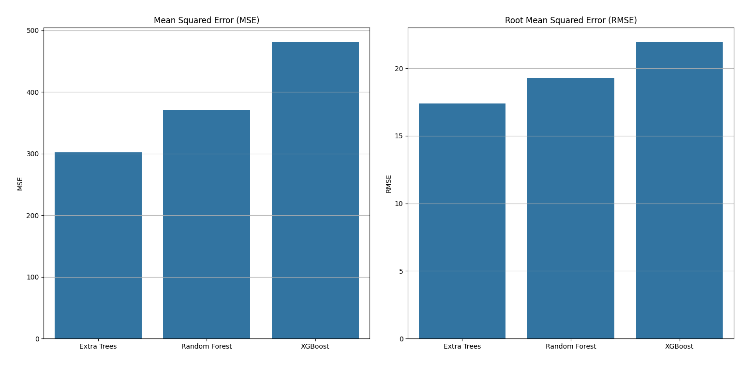


Fig 5 RMSE and MSE of used ensemble models

The RMSE plot shows the model's prediction error as magnitude, in the same units as the target variable. RMSE is a very common performance metric in regression problems since it weights larger errors more heavily because differences are squared. This makes it particularly valuable where large deviations are worse than small ones. A lower RMSE shows improved model performance, with smaller large prediction errors. The associated plot provides a means of seeing how the RMSE differs between various models or between different phases of tuning, offering a concrete means of measuring improvement. Because RMSE is a measure sensitive to outliers, an unexpectedly high value may suggest the existence of such outlier values that are skewing the model's accuracy. Whereas R² is a relative measure, RMSE provides us with an absolute estimate of how far from the truth our predictions are, on average. This makes it priceless in gauging the model's applicability in real life — particularly when converting predictive outcomes into concrete decisions.

**Conclusion**

In this research, there was full cross-validation of the regression model with various statistical and graphical measures of performance and readability. Important measures like the R² score and RMSE were all used to make sure that the model could properly represent underlying data trends as well as provide good predictions. The predicted vs. actual values indicated a high trend, and with no apparent bias and also good generalization power. The residuals also gave some indication of randomly scattered model errors around zero, indicating no significant overfitting or underfitting. The feature importance plot also gave information regarding the contribution of each feature towards model output, important for interpretability and real-world decision-making. In summary, the above results confirm and validate the robustness of the model in the current situation.

In this study, the regression model was fully cross-validated by employing different measures of performance and readability statistics as well as plots. Key performance measures such as the R² score and RMSE ensured the model was successful in capturing underlying data trends and making decent predictions. Predicted versus actual values showed a strong trend, along with no discernible bias, and good ability to generalize. TWhile the model shows solid performance, several changes can be done to improve even more on performance as well as adjustability. One improvement direction could be implementing the incorporation of utilizing higher-end ensemble learning techniques, i.e., stacking or boosting based on neural networks, for learning sophisticated non-linear relationships between the data. In addition, the incorporation of Explainable AI (XAI) methods like SHAP or LIME can provide more insights into the individual forecasts, and thus improve transparency and trustworthiness of the model. On a data level, the addition of newer and more diverse records to the dataset may improve generalizability, and data quality and usefulness may be improved with outlier detection and feature engineering. Finally, translating the model to a real-time or interactive web-based environment can provide dynamic feedback and enhance its usability in actual decision support systems. e residuals also provided some hint of randomly scattered errors of the model around zero, indicating minimal overfitting or underfitting. The feature importance plot also provided information about contribution of every feature towards model output, useful for interpretability and actual decision-making. Collectively, these findings reaffirm and authenticate the stability of the model within the existing climate.

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