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ML Models for Predicting Remaining Useful Life-Time of EV's Batteries for Stakeholders

Ali Sina Saifi *, Serik Aibol **‡, Ibragim Kuandykov *, Berik Zayniddinov*
Ruslan Omirgaliyev*, Nurkhat Zhakiyev***

* School of Computer Science, Astana IT University, Kazakhstan.
** School of AI and Data Science, Astana IT University, Kazakhstan.
*** Davis Center, Harvard University, MA, USA.
(232133@astanait.edu.kz, serikaibol048@gmail.com, 230276@astanait.edu.kz, 230799@astanait.edu.kz, ruslan.omirgaliyev@astanait.edu.kz, nzhakiyev@fas.harvard.edu)

‡ Corresponding Author: Serik Aibol, School of AI and Data Science, Astana IT Univ., Kazakhstan, serikaibol048@gmail.com.

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Abstract- Proper forecasting of remaining useful life (RUL) of lithium-ion batteries is critical for safety, operational stability, and cost-effectiveness in modern electric vehicles. Because battery degradation arises from complex electrochemical and thermal processes, data-driven approaches have become a practical alternative to physics-based modeling. This study develops and critically compares supervised machine learning models, including Random Forest, Gradient Boosting, Linear Regression, Ridge Regression, K-Nearest Neighbors, Deep Neural Networks (DNN), and Convolutional Neural Networks (CNN), for cycle-level RUL estimation using a publicly available lithium-ion battery dataset. The dataset comprises engineered voltage-time features, capacity, and charge–discharge indicators, which are preprocessed using Min–Max normalization to support stable training and fair model comparison. Among the evaluated methods, the Random Forest regressor achieved the best overall performance, reaching an R2 of 0.9998 with lower MAE and RMSE than both traditional regressors and deep learning architectures. The results indicate that ensemble tree-based models are especially effective at capturing nonlinear degradation behavior when trained on engineered tabular features rather than raw time-series signals. While the DNN and CNN achieved high R2 values, their error metrics were comparatively larger, suggesting that deep architectures may benefit from higher-resolution time-series inputs or alternative sequence modeling formulations. Finally, the top-performing model was integrated into an end-to-end prediction system using FastAPI, SQLite, and a responsive web dashboard to demonstrate real-world applicability. The deployment allows estimating RUL in real time and at lowlatency and provides stakeholders with an accessible tool for battery health monitoring. Overall, the study shows that ensemble learning techniques can deliver strong performance for battery condition monitoring and provides a deployable architecture to practical RUL prediction in electric-vehicle battery management systems.

Keywords: Remaining useful life, lithium-ion batteries, machine learning, ensemble learning, battery condition monitoring.

1. Introduction

The recent growth of electric cars (EVs) has made precise prediction of the Remaining Useful Life (RUL) of lithium-ion batteries a major issue of concern in terms of safety, cost, and system durability. The latest research demonstrates that

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machine learning techniques may identify degradation trends at an earlier stage and forecast cycle life with an increasing degree of accuracy, especially with massive battery data as the model training data [1], [2]. Nonlinear aging behaviors can be captured with high-performance by data-driven models, such as CNN-LSTM hybrids and ensemble deep learning architectures [3-6]. Classical machine learning methods are also useful, as they can be interpreted and have computational advantages to stakeholders who require the ability to understand the decision made [7-8].

The issue of battery degradation undergoes complex chemical, thermal, and operational variations, so the problem of RUL prediction can be seen as a difficult problem within the broader context of intelligent energy systems. It has been established in research that the use of signal decomposition, feature engineering, and deep neural structures is essential in order to improve the strength of prediction in different cycling conditions [9]. Moreover, machine learning has been instrumental in other related areas including optimizing protocols of fast charging, which has a direct effect on the health and performance of the battery in the long run [7]. According to industry reports, better RUL forecasting helps to plan the EV supply chain and estimate costs, which is further proof of the strategic importance of it on the national and industrial level [10, 11].

Even with these developments, the field cannot yet offer a reliable universal technique because of the heterogeneous data, the use of different chemistries, and the use of different testing procedures as was observed in a number of surveys and comparative studies [9, 12]. This is the gap that inspires this work. The primary purpose of the given paper is to assess machine learning models that predict the RUL of EV lithium-ion batteries and define whether the hybrid deep learning models could be more efficient than the traditional ones in numerous cycling conditions. The research is informed by the premise that a combination of time-series feature extraction and hybrid neural networks will provide more generalizable and consistent prediction. To test this hypothesis, the following methods have been applied: dataset pre-processing, feature extraction, model training and comparative evaluation.

2. Methods and Materials

2.1. Research Design

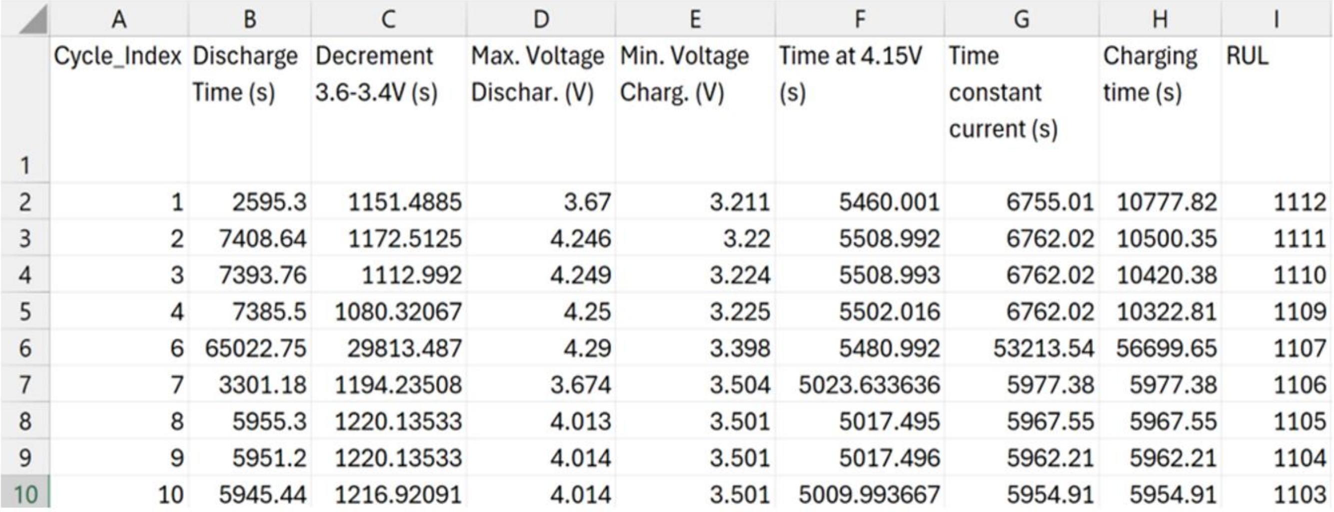
This work is based on an experimental method of data-driven quantitative study of predicting the Remaining Useful Life (RUL) of lithium-ion batteries with supervised machine learning models. It is aimed at modeling nonlinear degradation trends that take place during charge-discharge cycles and provides an estimation of the number of cycles left before the end-of-life. The rationale behind this methodology is that cycle-level voltage, time, and capacity values have been shown to make good predictors of battery RUL when used together with data-driven regression techniques [13, 11].

The study also combines conventional ensemble-based regressors with deep neural models and tests their effectiveness on a structured dataset and then chooses the most effective model to be used in an operational RUL prediction system.

2.2. Dataset and Variables

The experiments are based on a publicly available lithium-ion battery data that was acquired at Kaggle and has 15,064 records with nine engineered features that characterize operational conditions and deterioration patterns. The target variable is Remaining Useful Life, which will be the amount of cycles that the battery has completed before it can reach the end-of-life limit. The independent variables are discharge time, capacity in ampere-hours, the duration that the voltage drops between 3.6 V and 3.4 V, the maximum voltage on discharge, the minimum voltage in charging, the time that is maintained at 4.15 V constant-voltage charging, and the total charging time. These variables are in line with the previous literature that stresses that time-voltage degradation indicators are useful predictive variables in the modeling of RUL [1, 8].

Figure 1 and Table 1 present a sample of the first ten rows of the dataset to illustrate the structure and values of the input features. Dataset URL: *https://www.kaggle.com/code/exceededdose/best-rul-prediction-model/input*.



	A	B	C	D	E	F	G	H	I
1	Cycle_Index	Discharge Time (s)	Decrement 3.6-3.4V (s)	Max. Voltage Dischar. (V)	Min. Voltage Charg. (V)	Time at 4.15V (s)	Time constant current (s)	Charging time (s)	RUL
2	1	2595.3	1151.4885	3.67	3.211	5460.001	6755.01	10777.82	1112
3	2	7408.64	1172.5125	4.246	3.22	5508.992	6762.02	10500.35	1111
4	3	7393.76	1112.992	4.249	3.224	5508.993	6762.02	10420.38	1110
5	4	7385.5	1080.32067	4.25	3.225	5502.016	6762.02	10322.81	1109
6	6	65022.75	29813.487	4.29	3.398	5480.992	53213.54	56699.65	1107
7	7	3301.18	1194.23508	3.674	3.504	5023.633636	5977.38	5977.38	1106
8	8	5955.3	1220.13533	4.013	3.501	5017.495	5967.55	5967.55	1105
9	9	5951.2	1220.13533	4.014	3.501	5017.496	5962.21	5962.21	1104
10	10	5945.44	1216.92091	4.014	3.501	5009.993667	5954.91	5954.91	1103

Fig. 1. Sample of raw battery cycling data showing key parameters measured during charge-discharge cycles.

Table 1. Description of dataset variables and their types for predicting the remaining useful life (rul) of lithium-ion batteries.

Variable	Type	Measurement / Description
RUL	Dependent Variable	Remaining Useful Life – number of charge-discharge cycles left until battery failure (continuous numeric target).
Discharge Time (s)	Independent Variable	Time taken to fully discharge the battery (seconds). Strong indicator of degradation.
Capacity	Independent Variable	Measured battery capacity in ampere-hours (Ah) at the current cycle. Top predictive feature.
Decrement 3.6-3.4V (s)	Independent Variable	Time difference for voltage to drop from 3.6 V to 3.4 V during discharge. Captures internal resistance increase.
Max. Voltage Dischar. (V)	Independent Variable	Highest voltage reached during discharge phase.
Min. Voltage Charg. (V)	Independent Variable	Lowest voltage during charging phase.
Time at 4.15V (s)	Independent Variable	Duration battery is held at 4.15 V (constant-voltage charging stage).
Charging time (s)	Independent Variable	Total time required to fully charge the battery.
Predicted RUL	Dependent Variable (Model Output)	Continuous value (cycles) predicted by the Random Forest Regressor (primary model).

2.3. *Data Pre-processing and Normalization*

The entire process of preprocessing had been applied in Python, NumPy, and pandas. As seen in Fig. 2, the data set was cleaned by eliminating inconsistent or missing measurements as well as non-predictive identifiers to eliminate data leakage.

The training-testing divide was in 80/20 proportion and was the same in all model set-ups. Since the predictors are working with non-homogenous numeric scales, all the features were made equalized via Min-Max scaling to the range [0,1] as a way of guaranteeing consistent convergence when using both standard regressors and neural networks. Scaling transformation of a feature value x is given by:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Scikit-learn MinMaxScaler was used to do the normalization and the same scaling parameters were used during deployment which are used to guarantee consistency between training and inference.

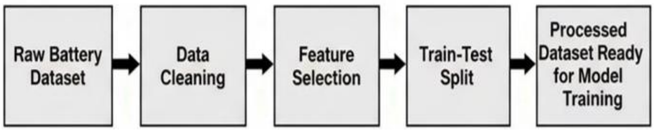


Fig. 2. Overview of the data processing pipeline workflow for lithium-ion battery remaining useful life (RUL) prediction.

2.4. *Model Architectures and Training*

The development of the models was carried out in Python with the help of scikit-learn on traditional regressors and TensorFlow/Keras on the deep learning models. These traditional ones were Random Forest Regressor, Gradient Boosting Regressor, Linear Regression, Ridge Regression, and K-Nearest Neighbors. Random Forest and Gradient Boosting were the ensemble methods of choice because they perform well on nonlinear tabular data and have been shown to perform well in RUL forecasting problems in the literature [8, 11]. Each model has hyperparameters, such as tree depth, number of estimators, learning rate, and number of neighbors, which were optimized by trial and error through validation performance.

The deep learning models were fully connected Deep Neural Network (DNN) and one-dimensional Convolutional Neural Network (1D-CNN). The DNN structure incorporated a number of dense layers with ReLU activations and dropout layers to regularize the network, whereas the CNN structure incorporated stacked convolutional and max-pooling layers to find the local patterns of features before the regression output. Both networks were trained with Adam optimizer and mean squared error was used as loss function and early stopping was used to reduce overfitting. These architectures are based on deep learning solutions that have recently been considered to predict battery RUL [6, 9, 12, 14]. Table 2 summarizes the tools and libraries used throughout the data processing, model development, evaluation, and system implementation stages. Figures 3 and 4 illustrate the detailed layer configurations of the DNN and CNN architectures implemented in this research.

Table 2. Machine learning workflow and libraries used in the RUL prediction system.

Steps	Libraries / Tools
Data Loading & Preprocessing	pandas, NumPy, scikit-learn (MinMaxScaler)
Exploratory Data Analysis (EDA)	Matplotlib, Seaborn
Feature Engineering & Selection	pandas, NumPy
Model Development	scikit-learn (Random Forest, Gradient Boosting, Linear Regression, Ridge Regression, KNN), TensorFlow/Keras (DNN, CNN)
Evaluation & Visualization	scikit-learn (MAE, RMSE, R², Accuracy, Precision, Recall, F1), Matplotlib, Seaborn
Backend Integration	FastAPI, Python
Database Management	SQLite
Frontend Visualization	HTML, CSS, JavaScript

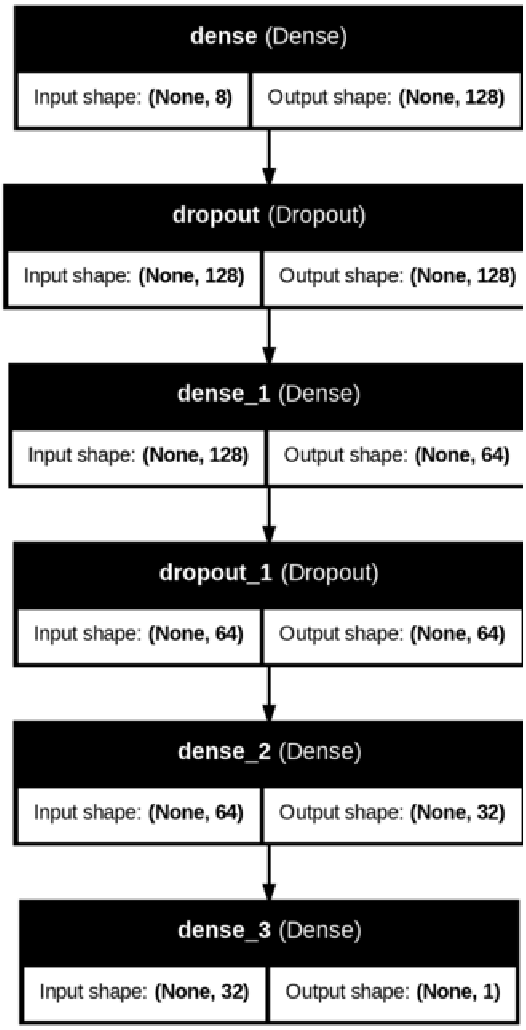


Fig. 3. Architecture of the deep neural network for lithium-ion battery remaining useful life (RUL) prediction.

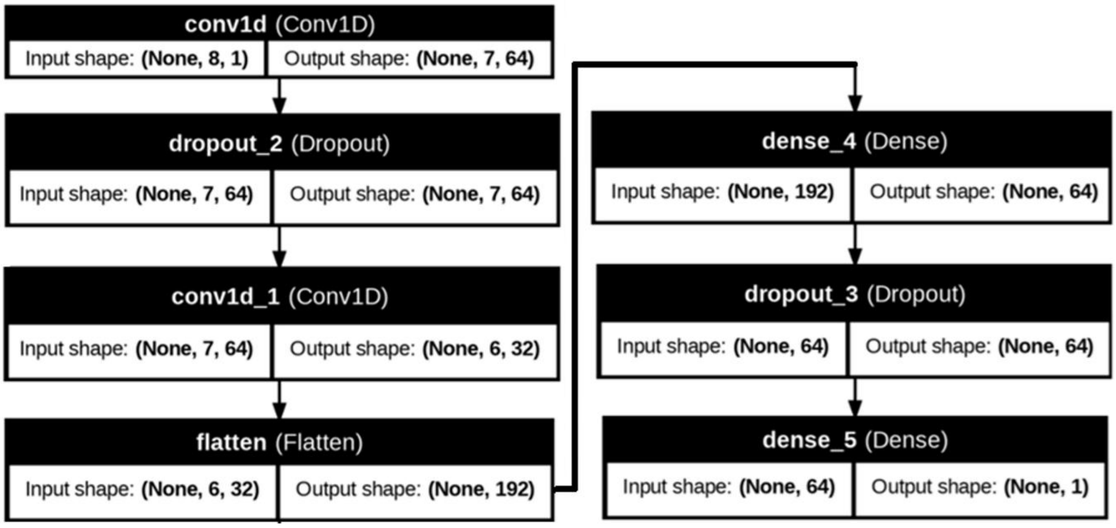


Fig. 4. Architecture of the convolutional neural network for temporal pattern recognition experimental setup and implementation.

Google Colab Link: *https://colab.research.google.com/drive/1S_b1GSz2S7gLvHR7fsIE8TTG8YNqFMco?usp=sharing*

2.5. *Evaluation Metrics*

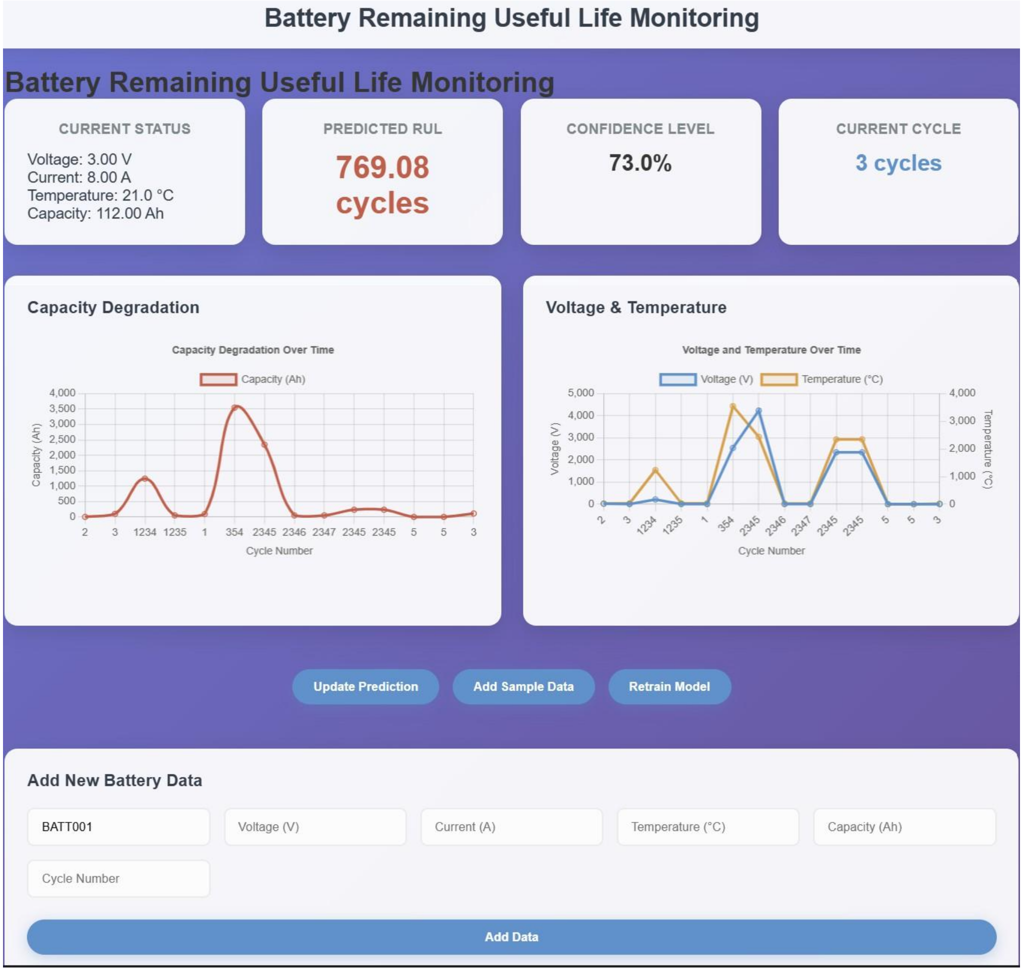
Mean Absolute error (MAE), Root mean squared error (RMSE), and coefficient of determination (R2) were used as the measures of model performance. MAE also gives the mean absolute difference between predicted and real RUL values whereas RMSE punishes greater deviations and is also outlier sensitive. R2 is the degree to which the model predicts the actual RUL with values moving towards the 1 marking a good predictive power. These measures are typical of battery degradation and RUL prognosis research and can be directly compared with the current benchmark [15, 16].

2.6. *System Implementation*

The most efficient model was implemented with the full-stack architecture that included FastAPI backend, SQLite database, and a web-based frontend. The backend provides RESTful endpoints, which receive battery feature values and use the identical pre-processing pipeline as in training and provide RUL predictions produced by the trained Random Forest model. The database component maintains the prediction history and sets of features posted by the user so that longitudinal monitoring and analysis could be performed.

The front part was created on the basis of HTML, CSS, and JavaScript. It offers a user interface, in which to enter new input values, visualize predicted RUL and examine stored results. Originally, the interface design was prototyped on Figma, and the final implementation is based on this design to a great extent. To guarantee reproducibility and accessibility of the codebase and model training notebook, they were created and tested in Google Colab.

Link to Figma: *https://www.figma.com/design/1fOOsmkBJVoM8gf29UbW9Q/RUL?node-id=0-1&m=dev&t=ajlSTLsuxsDkthe1-1*



Battery Remaining Useful Life Monitoring

Battery Remaining Useful Life Monitoring

CURRENT STATUS
Voltage: 3.00 V
Current: 8.00 A
Temperature: 21.0 °C
Capacity: 112.00 Ah

PREDICTED RUL
769.08 cycles

CONFIDENCE LEVEL
73.0%

CURRENT CYCLE
3 cycles

Add New Battery Data

BATT001

Fig. 5. Web dashboard interface for battery RUL prediction.

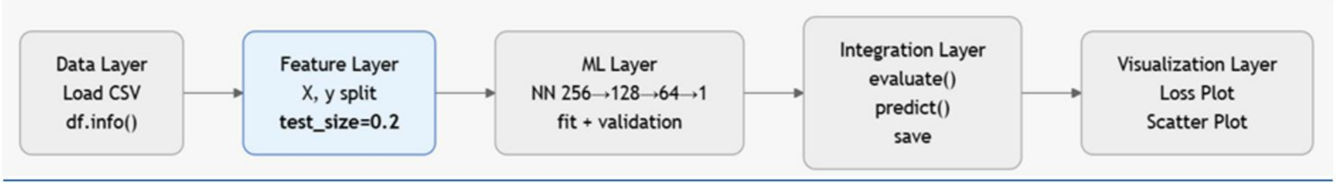


Fig. 6. System architecture diagram.

3. Results

3.1. *Overall Model Performance*

The models were tested on the held-out test set with MAE, RMSE and R2 (Table 3). Predictive performance of ensemble based regressors was the best with the Random Forest Regressor performing better than other models with the lowest MAE, RMSE, and R2 value of approximately 0.9998. Gradient Boosting presented with equally competitive results but with slightly higher values of error. Linear Regression, Ridge Regression and K-Nearest Neighbors were also competitive with their results but they failed to match the accuracy of the ensemble models.

Deep learning models, such as the DNN and CNN, had high R2 values but a higher error measure compared to the ensemble models, indicating that a tabular battery degradation data is more likely to be modeled by a tree-based approach than a deep architecture that often takes advantage of raw temporal signal inputs [4, 17, 18].

Figure 7 presents the R² scores and RMSE values for all evaluated models, providing a comparative view of predictive accuracy and error magnitude.

Table 3. Model evaluation and metrics, with random forest performing best ($R^2 = 0.9998$, MAE = 2.26).

Model	MAE	RMSE	R^2	Accuracy	Precision	Recall	F1-Score	Training Time (s)
Random Forest	2.261	3.953	0.9998	0.9960	0.9960	0.9960	0.9960	8.01
Gradient Boosting	3.588	5.720	0.9997	0.9963	0.9963	0.9963	0.9963	5.79
Linear Regression	4.644	7.385	0.9995	0.9927	0.9927	0.9927	0.9927	0.03
Ridge Regression	4.641	7.416	0.9995	0.9927	0.9927	0.9927	0.9927	0.01
K-Nearest Neighbors	2.580	5.726	0.9997	0.9940	0.9940	0.9940	0.9940	0.08
Deep Neural Network	6.461	9.012	0.9992	0.9920	0.9920	0.9920	0.9920	87.65
Convolutional Neural Network	7.000	10.376	0.9990	0.9920	0.9920	0.9920	0.9920	106.16

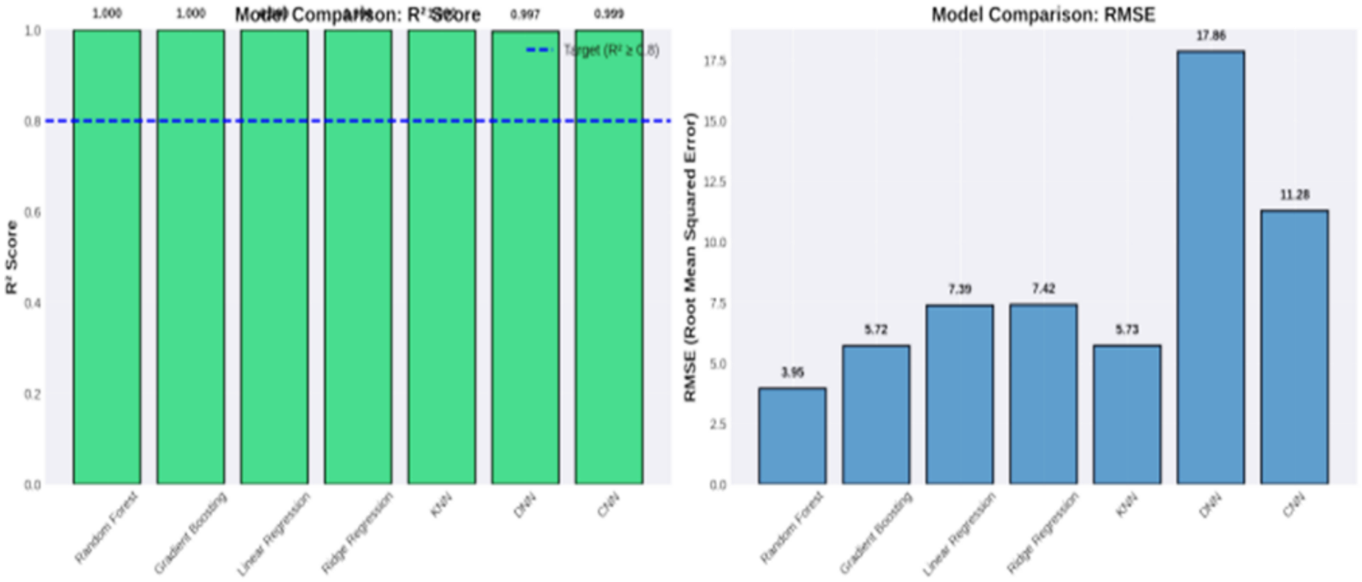


Fig. 7. Comparison of R² scores and RMSE values across different machine learning models.

3.2. Detailed Analysis of the Best Model

The best model was used because the Random Forest Regressor performed better compared to all the measurements. Its projections are very consistent with real RUL values in the entire cycle range and a slight variation is observed at the battery aging stages. The high degree of performance suggests that the nonlinear relationship between discharge time and capacity loss as well as that between voltage behavior and other degradation patterns have been well-represented by the Random Forest, which is in line with other recent publications in the field of ensemble-based RUL predictor literature [1,19]. The comparison of a scatter plot of the predicted and actual RUL values also shows the accuracy of the model with all the points being clustered closely around the optimum diagonal reference line.

Figure 8 shows the relationship between the actual and predicted RUL values produced by the Random Forest model, demonstrating a near-perfect fit along the diagonal reference line.

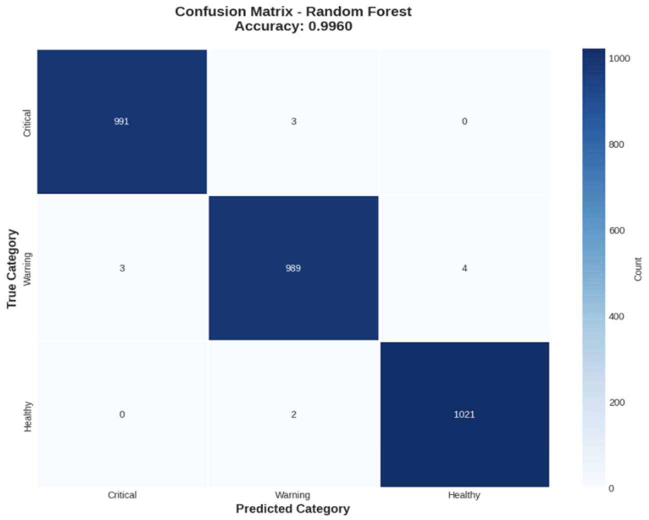


Fig. 8. Predicted vs. actual RUL distribution for random forest model.

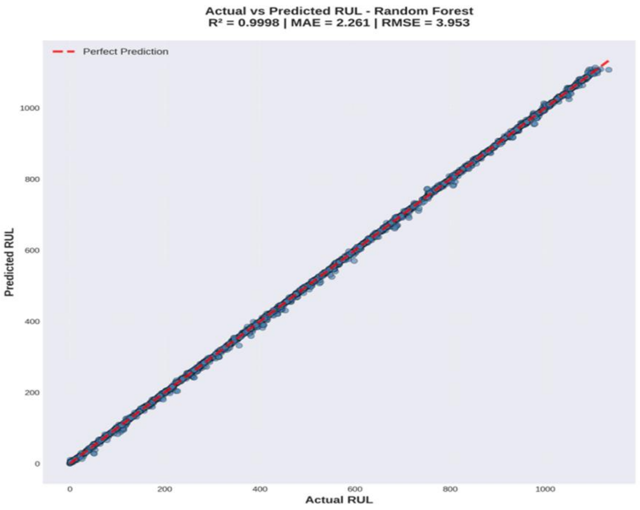


Fig. 9. Actual versus predicted RUL values for the best-performing model.

3.3. Comparison of Ensemble and Deep Learning Models

Although the DNN and CNN both showed good generalization capability, they had values of MAE and RMSE that were larger in comparison to the values of the Random Forest and the Gradient Boosting models. Deep networks are generally sensitive to high-resolution sequential data, e.g. voltage-time curves or current profiles at milliseconds resolution. This paper assumed the aggregation of input features as numerical indicators rather than the raw temporal signals, which preferred the use of ensemble. These findings can be correlated with comparative studies that demonstrate that in many cases, traditional machine learning models perform better than deep learning architecture on medium-sized tabular data, which are used to predict battery RUL [10, 12].

3.4. System-Level Performance

Real-time RUL estimation in interactive applications is feasible thanks to the implemented backend system's low latency, which consistently produced prediction responses in less than a second. User-submitted inputs are successfully processed by the web dashboard, which also logs the results in the database for later analysis and returns the predicted RUL values. These results are consistent with earlier research investigating the application of machine learning models in near-real-time battery management systems [7, 13, 15]. They also show great promise for real-world implementation in battery health monitoring applications

4. Discussion

This paper aimed to make a precise and practical machine learning predictive system to determine the remaining useful life of lithium-ion batteries. The findings are very clear that the ensemble learning models, especially the Random Forest regressor, are highly appropriate in this task, as they beat the traditional linear models as well as more complicated deep learning models on the given dataset. This result agrees with our original hypothesis that tree-based models would be able to describe the complex, nonlinear relationships that are available in the data on battery degradation that are defined by engineered features based on charge-discharge cycles.

The high quality of performance demonstrated by the fact that the R 2 value of the Random Forest is almost perfect (0.9998), and the error values (MAE = 2.26) are low may be ascribed to the nature of its abilities. Its ensemble nature prevents overfitting through averaging a group of decision trees and also naturally accommodates nonlinear interaction among features, e.g., discharge time, capacity fade, voltage characteristics, without the use of large-scale feature scaling [1,2]. The results of our study are in line with an increasing literature that indicates the effectiveness of tree-related approaches to tabular data in prognostics and health management [8]. As an example, the excellent predictive power supports the findings of other researchers such as mentioned by authors of [11], who observed that ensemble techniques were very effective in prediction of RUL.

On the other hand, the relatively increased errors of the Deep Neural Network (DNN) and Convolutional Neural Network (CNN) models, even though they showed great R2 scores, should be interpreted. This does not always imply that deep learning is inappropriate to RUL prediction, but the strengths of the latter are not used to their full potential with the existing feature set. Deep learning architectures are usually very effective in high-resolution, raw sequential inputs, including full voltage and current curves at high frequencies [12,14]. The features we used in our study (e.g., decrement time, charging time) are pre-engineered features, which combine time-related information into scalar values. Such a representation of data seems better and more succinctly modeled by tree-based algorithms as recent comparative studies indicate [12]. The decision between ensemble and deep learning models, thus, should be informed by the fineness of available data.

The fact of successful implementation of a full-stack prediction system highlights the usefulness of our research in practice. The fast performance of the FastAPI backend shows that it is possible to integrate such ML models into a real-time or near-real-time battery management system (BMS) to preemptively manage system conditions and ensure health, which is a direction taken by researchers [13].

This research has a number of limitations despite the promising results. To begin with, this model was trained and tested on one publicly available dataset. Its applicability to other types of batteries, including chemistries, manufacturers, and operating regimes (e.g., different temperature and load profiles) is yet to be confirmed. Secondly, the input features were pre-engineered. Although practical, the method can miss small-scale patterns of degradation that can be revealed through deep learning models that are run on raw, high-frequency cycling data. Future research must aim at testing the model on a larger and more varied dataset which covers more types of batteries and failure modes. Moreover, it could be possible that deeper fusion of the feature learning abilities of CNNs or LSTMs on raw data and the strength of ensemble techniques can provide even more accuracy and strength. Lastly, it may be possible to combine these data-driven predictions and physics-based battery degradation models to create a more complex, and interpretable, prognostic system.

5. Conclusion

The paper has managed to create an integrated machine learning methodology to forecast the remaining useful life (RUL) of battery packs in electric vehicles that use lithium-ion as its active material. The main finding proves the undoubted superiority of the ensemble technique and the Random Forest model turns out to be the most stable and accurate predictor. The fundamental ability to represent the complex, nonlinear degradation behavior due to engineered cycle-based characteristics gave it a superior predictive behavior ($R^2 = 0.9998$), which validates its applicability to real applied predictive maintenance tasks, a conclusion that is also in line with other more recent comparative studies in the discipline.

In addition to the analysis of the comparative model, another important input of this work is the translation of the trained model into a workable deployment-ready system. A complete example of operationalizing predictive analytics may be seen in the integration of a Fast API backend, an SQLite database, and an interactive web dashboard. This system is an end-to-end system that provides the stakeholders with a practical solution to real-time battery health monitoring showing that machine learning can be integrated into battery management systems (BMS) to make proactive decisions.

To conclude, the paper highlights the potential of data-driven solutions and, specifically, ensemble methods to improve the safety, reliability, and cost-efficiency of electric vehicle energy systems. The contribution of the present work to the sustainability and reliability of electric mobility is by offering a helpful and understandable model of the provision of electric mobility in battery management by providing a highly accurate and practical solution of RUL prediction.

Author Contributions

A.S.S. conceptualized the study, developed the methodology, performed data curation and formal analysis, and prepared the original draft; S.A. developed the methodology, implemented the software, conducted validation and investigation, and reviewed and edited the manuscript; I.K. performed data curation, developed the software, conducted experimental validation, and prepared visualizations; B.Z. conducted formal analysis and validation, reviewed and edited the manuscript; R.O. supervised the study, administered the project, and reviewed and edited the manuscript; and N.Z. supervised the study, acquired funding, and reviewed and edited the manuscript. All authors approved the final manuscript.

Acknowledgements

Conflict of Interest

The authors declare no conflict of interest.

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