Email: editor@ijerst.com or editor.ijerst@gmail.com

International Journal of Engineering Research and Science & Technology

https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472

ISSN 2319-5991 www.ijerst.com

Vol. 21, Issue 2, 2025

MACHINE LEARNING BASED PREDICTION OF REMAINING USEFUL LIFE IN EV BATTERIES

[1] *Mohammed Abdul Imran, MCA Student, Department of MCA*

[2] *B.Harish Kumar Reddy, M.Tech, (Ph.D), Assistant Professor, Department of MCA*

[12] *Dr KV Subba Reddy Institute of Technology, Dupadu, Kurnool*

ABSTRACT

One important way to fight increasing carbon emissions and lessen reliance on fossil fuels is by using electric cars, or EVs. To encourage EV adoption, the Indian government has put regulations in place including the Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) initiative. Machine learning-based EV battery Remaining Useful Life (RUL) prediction improves operating efficiency and guarantees improved battery health management. EV fleet management, battery recycling, and economical maintenance are a few examples of applications. To enhance operational dependability, save maintenance costs, and promote sustainable energy habits by creating a machine learning model that reliably forecasts the Remaining Useful Life (RUL) of EV batteries. Prior to the development of machine learning, conventional techniques for predicting the lifespan of EV batteries were based on rule-based methodologies, in which battery health was predicted by predetermined criteria like voltage decreases or charge cycles. Frequently linear, empirical models were created using past performance data but were unable to adjust to changing use patterns. Furthermore, manual battery testing was a popular method of assessing deterioration, despite the fact that it was labour-intensive, time-consuming, and often prone to errors in capturing the intricate nature of battery ageing. The majority of traditional EV battery life prediction methods are empirical in nature and use static models that are unable to account for dynamic battery behaviour. These techniques often result in inefficient battery management since they are labour-intensive, imprecise, and provide no flexibility to changing use circumstances. The necessity for precise RUL prediction systems is fuelled by the growing demand for EVs and their crucial reliance on battery performance. Because battery deterioration is complicated and non-linear, traditional approaches are inadequate. The suggested machine learning-based method trains predictive models that can estimate the Remaining Useful Life (RUL) of EV batteries using real-time battery performance data, such as voltage, current, temperature, and charge-discharge cycles. This method greatly improves accuracy by identifying intricate patterns in battery deterioration, permits real-time forecasting for instant insights, minimises needless replacements and maximises resource use, and fosters sustainability through effective recycling and decreased battery waste.

I. INTRODUCTION

In order to solve global environmental concerns, electric vehicles (EVs) are becoming a viable option for lowering carbon emissions and reducing reliance on fossil fuels. India has launched programs like the FAME plan to encourage EV adoption as part of its sustainable energy ambitions. According to statistics, India wants to electrify 30% of its fleet of vehicles by 2030. Over the last five years, EV sales have increased at a compound annual growth rate (CAGR) of 49%. The main difficulty, nonetheless, is guaranteeing battery dependability since unplanned battery failure affects customer confidence in addition to raising expenses. A revolutionary way to address these issues is to use machine learning to predict the Remaining Useful Life (RUL) of EV batteries, guaranteeing increased operational effectiveness, improved resource use, and sustainability.

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472
Vol. 21, Issue 2, 2025

Estimating an EV battery's Remaining Useful Life (RUL) reduces unplanned failures and guarantees efficient battery health management. Accurate forecasts from machine learning models enhance battery recycling, EV fleet operations, and economical maintenance. Applications include managing battery warranty programs, streamlining EV fleet logistics, and facilitating predictive maintenance for commercial EV fleets.

1.2 Problem Definition

Traditional EV battery life prediction methods had a number of drawbacks prior to using machine learning. Dynamic battery behaviours were not taken into consideration by rule-based approaches, which depended on fixed thresholds like voltage dips or charge cycles. Empirical models only provided linear approximations and were not flexible enough to adjust to real-time consumption patterns. Manual testing techniques were not appropriate for large-scale battery management because they were labour-intensive, resource-intensive, and prone to mistakes. These methods resulted in ineffective maintenance plans, increased operating expenses, and a lack of understanding of the dynamics of battery deterioration.

1.3 Research Motivation

The EV industry's rapid expansion emphasises how important battery health is to guaranteeing dependability and efficiency. The accuracy and flexibility required to forecast battery life are not provided by conventional techniques. By examining intricate and non-linear deterioration patterns, machine learning advancements provide the possibility of resolving these issues. Leveraging these characteristics to maximise battery performance, save costs, and support sustainable energy practices is what motivates this study. Furthermore, precise RUL forecasts may increase customer trust in EV technology.

1.4 Existing Systems and Drawbacks

Manual testing, empirical models, and rule-based systems were among the conventional techniques used to estimate EV battery life. Although these techniques offered fundamental information about battery health, they were imprecise and unresponsive to changing use circumstances. Manual testing was ineffective for large-scale applications, rule-based methods were very strict, and empirical models were unable to account for non-linear deterioration. These shortcomings led to inaccurate forecasts, higher maintenance expenses, and needless battery replacements.

1.5 Proposed System

A machine learning model trained on real-time battery performance data, including voltage, current, temperature, and charge-discharge cycles, is developed as part of the suggested system. To capture intricate deterioration patterns and provide precise RUL forecasts, sophisticated machine learning approaches such as bagging and decision trees are used. Research articles like "Data-Driven Predictive Models for EV Battery Health" and "Machine Learning Approaches for Battery Lifetime Prediction" provide a solid basis for putting such a system into practice. The model enhances EV battery lifetime management by combining real-time monitoring, predictive analysis, and decision-making capabilities.

1.6 Real-Time Need

As EV usage rises, effective battery lifetime management is necessary to guarantee dependability and customer happiness. Unpredictable battery problems may lower the operating efficiency of EV fleets by causing expensive downtime. For preventive maintenance and replacement scheduling, accurate RUL forecasts are essential. This initiative reduces battery waste and improves recycling methods, which supports India's drive for sustainable energy. It addresses battery disposal's negative environmental effects and supports circular economy projects. Additionally, real-time RUL predictors help

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472
Vol. 21, Issue 2, 2025

EV manufacturers optimise their product development and warranty programs.

1.7 Applications

1. Fleet Management: Reduces downtime and boosts operational efficiency by enabling predictive maintenance for EV fleets.
2. Battery Recycling: Encourages environmental sustainability by making it easier to recycle batteries on time.
3. Cost Optimisation: Lowers needless battery replacements and maximises lifespan expenses.
4. Battery Warranty Programs: Assists EV producers in providing accurate and dependable warranty schemes.
5. Consumer Insights: Encourages trust in EV technology by giving EV owners real-time battery status data.
6. Sustainability: Integrates effective battery recycling and reuse techniques to support a circular economy.
7. Energy Storage Systems: Assists in determining if spent EV batteries may be recycled for energy storage applications.
8. Policy Development: Provides information to legislators so they may create rules for recycling and battery lifetime management.

II. LITERATURE SURVEY

The fast growth of electrical cars powered by renewable energy is a defining feature of this electrification age. The rise in renewable energy-based systems has significantly enhanced the importance of energy storage systems. Because of its strong power output, low self-discharge rates, and high energy density, Li-ion batteries are regarded as being better than alternative energy storage technologies [1], [2]. The growing importance of this problem necessitates greater requirements and challenges for battery management technology advancement. Data collection, status analysis and forecasting, charging and discharging control, safety features, thermal management, power balancing, and communication systems are all components of a comprehensive battery management system (BMS) [3]. A BMS's accuracy in estimating the state is a measure of its efficiency. An outstanding BMS extends battery life and guarantees the energy storage system's steady operation [4]. A real-time operating system and multitasking abilities are essential for a BMS that allows for continuous monitoring and quick changes. Despite their benefits, lithium-ion batteries have limitations that keep them from being widely used, most notably their cost and lifetime [5]. Calendar ageing and cycle ageing cause battery performance to decline over time, resulting in many degradation events [6], [7]. In addition to increasing operating expenses, ageing shortens equipment lifespans and compromises safety [8, 9, 10]. When a battery's capacity drops to 80% of its original value, it is often considered to have reached the end of its useful life [11]. The anticipated operating duration from the present moment until the battery reaches its end-of-life is known as the Remaining Useful Lifetime (RUL) [12], [13], and [14]. The battery's lifespan is determined by its composition and the chemical changes that take place inside it throughout charge-discharge cycles. The complex and non-linear ageing process is further influenced by environmental factors, charge/discharge rates, and temperature [15], [16], [17], and [18]. One of the most difficult tasks is accurately predicting RUL in complicated settings. Accurate RUL forecasts may reduce investment costs and increase profitability in industrial settings [19], [20]. Additionally, it improves safety, stability, and battery life in energy storage devices [21], [22]. Three prediction tactics are available in RUL: hybrid, data-driven, and model-based approaches. [23], [24]. The mathematical description of the internal battery physical and electrochemical response is developed in the

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472
Vol. 21, Issue 2, 2025

model-based method to provide prediction models that determine the battery's present state [25], [26], and [27]. Because parameterising electrochemical models requires the battery disassembly procedure, which is very difficult in real-world applications, the formulation of these models is a complicated process that confronts the issue of computing intensity. Once the model is ready, however, it demonstrates exceptional accuracy [28], [29]. At the same time, historical data is used to design data-driven techniques. Because of the complexity of the Li-battery, these data-driven techniques are thus more useful than the model-based approach [30], [31], and [32]. For electrical cars to operate as efficiently and safely as possible, the Remaining Useful Battery (RUL) projection is crucial. Thus, by modelling historical data using supervised learning techniques like Random Forest (RF) and Support Vector Machine (SVM), this research more precisely forecasts the remaining usable life of electrical car batteries. The NASA Ames Prognostics Centre of Excellence (PCoE) is the source of the historical battery data. Methods such as feature selection improve the models' accuracy. The study uses a variety of feature selection techniques, such as hyperparameter tuning and one-way ANOVA. The models' MSE and R2 values are used to determine whether models are successful. Obtaining real-time data on temperature variations and battery capacity reduction as a consequence of the investigation is innovative. Additionally, it shows the correlation between the percentage of battery decrease capacity and the number of cycles of battery use. Google Colab and a 12GB NVIDIA Tesla K80 GPU were used for this experiment in order to provide hardware acceleration. To pre-process and extract key characteristics, the dataset is divided into training and testing groups.

III. EXISTING SYSTEM

3.1 Overview of Traditional Systems

The Remaining Useful Life (RUL) of EV batteries was estimated using rule-based methods, empirical models, and manual testing prior to the development of artificial intelligence. Rule-based approaches evaluated battery health by using predetermined criteria, such as voltage loss, temperature increase, or certain charge-discharge cycle counts. These approaches ignored differences in use habits and contextual factors since they were oversimplified and often generalised.

Linear associations obtained from past battery performance data were used in empirical models. Although these models offered a fundamental comprehension of battery deterioration, they were unable to adequately represent the dynamic and non-linear character of actual battery ageing processes.

Additionally, metrics like internal resistance and capacity fading were often measured by hand testing. Usually, this procedure required testing in a lab setting and physical disassembly. This approach was time-consuming, resource-intensive, and unsuitable for real-time applications or large-scale battery management, even if it produced correct data in some situations.

These systems were insufficient for the demands of contemporary EVs as they lacked real-time monitoring and predictive capabilities. They were unable to flexibly adjust to a range of use scenarios, which led to less-than-ideal battery management techniques, higher maintenance expenses, and a greater chance of unplanned failures.

3.2 Limitations of Traditional Systems

1. Absence of Real-Time Monitoring: Inaccurate or delayed evaluations resulted from traditional approaches' inability to interpret real-time battery performance data.
2. Rigid Rule-Based Systems: Predictions made using fixed criteria were either too cautious or erroneous since they did not take into consideration the variety of

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472

Vol. 21, Issue 2, 2025

operational and environmental factors that affect battery health.

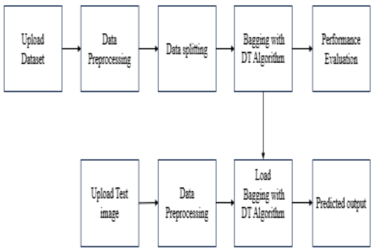
3. Incapacity to Manage Non-Linear Behaviour: The deterioration of batteries is a non-linear process that is impacted by a number of interrelated variables. These intricacies were beyond the scope of conventional linear models.
4. High Resource Intensity: Because manual testing took a lot of time and money, it wasn't appropriate for large-scale implementations or real-time applications.
5. Limited Scalability: Particularly in fleet management situations, traditional systems lacked the adaptability to adjust to the expanding size of EV adoption.
6. Imprecise Predictions: Instead of offering accurate insights, empirical models produced average estimations, which resulted in less-than-ideal maintenance schedules and needless expenses.
7. Environmental Impact: Sustainability initiatives were hampered by inefficient battery use and premature replacements, which increased electronic waste.
8. User Dissatisfaction: EV owners' trust and satisfaction were impacted by operational interruptions brought on by unexpected battery problems.
9. Labour-intensive Process: These systems were unsuitable for ongoing monitoring due to their dependency on manual testing and assessment.
10. Absence of Predictive Capabilities: Conventional systems addressed problems only after substantial deterioration had taken place since they were reactive rather than predictive.

IV. PROPOSED SYSTEM

4.1 Overview

Step 1: EV Battery Dataset

Getting a dataset with comprehensive data on EV battery performance is the first step in the process. Features including voltage, current, temperature, charge-discharge cycles, and capacity retention over time are often included in this information. It serves as the basis for training and evaluating machine learning models and data derived from publically accessible sources or actual battery testing trials.



Step 2: Dataset Preprocessing

Preprocessing the dataset is an essential step in guaranteeing the data's dependability and quality. It entails either deleting or imputing suitable values in order to handle missing or null data. Standardising the data to enhance model performance and scaling features for uniformity are additional preprocessing activities. To reduce noise in the dataset, this stage also entails locating and eliminating outliers.

Step 3: Existing Algorithms (SVR and DNN Regressor)

Existing methods such as Deep Neural Network (DNN) regressors and Support Vector Regressor (SVR) are used to create a baseline. While DNN employs a deep learning architecture to capture complicated non-linear correlations in the data, SVR is a robust model that translates data into higher dimensions for linear regression. These models' performance is evaluated to provide the suggested method a comparison standard.

Step 4: Proposed Algorithm (Bagging with Decision Tree Regressor)

To increase prediction accuracy, the suggested approach makes use of a Bagging ensemble in

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com

https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472

Vol. 21, Issue 2, 2025

conjunction with a Decision Tree Regressor. In order to improve resilience and lessen overfitting, this approach aggregates the results of many decision tree models. It is trained on the preprocessed dataset and is especially designed to deal with non-linear battery deterioration patterns.

Step 5: Performance Comparison

Standard performance indicators including Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared scores are used to assess the models. When compared to the baseline models (SVR and DNN), the suggested Bagging with Decision Tree Regressor shows a higher capacity to estimate the Remaining Useful Life (RUL) of EV batteries.

Step 6: Prediction of Output from Test Data

Predictions on test data are made using the trained Bagging with Decision Tree Regressor model. In order to estimate the RUL of EV batteries, the test dataset must be fed into the model. This provides precise, real-time information for efficient battery management.

4.2 Data Splitting & pre-processing

An essential stage in getting the dataset ready for machine learning is data preparation. Data splitting, which separates the dataset into training and testing subsets, is the initial step in this procedure. Usually, 20–30% of the data is set aside for testing, while 70–80% is utilised for training. By ensuring that the model is trained on a subset of the data and assessed on unknown data, this division aids in determining the model's capacity for generalisation. Verifying the dataset for null values is the next crucial step. Inaccurate predictions may result from null or missing values interfering with model training. The dataset is examined for any null values in order to remedy this, and suitable techniques are used. Imputation approaches, such as substituting the mean, median, or mode of the corresponding feature for nulls, are used to fill in the gaps when there are few missing data. Alternatively, if a row or column has too many missing values and doesn't meaningfully add to the model, it may be eliminated.

4.3 ML Model Building

Data loading and preprocessing, including managing missing values and encoding categorical data, are the first steps in creating an ML model. The dataset is then divided into testing and training sets. The issue determines which models (e.g., SVR, DNN, Bagging with Decision Trees) are used. Next, using the appropriate methods and hyperparameters, the model is trained on the training set. Performance measures including MAE, MSE, RMSE, and R2 are used to assess the model after training. By contrasting the projected values with the actual test set values, the prediction accuracy of the model is evaluated. For robustness, cross-validation may also be used. Once the model's performance is satisfactory, it may be stored for later use and predictions can be generated using test data that hasn't been seen yet. Performance may also be enhanced via hyperparameter adjustment. Lastly, anticipated and actual values are compared using visualisations such as scatter plots.

4.3.1 Existing Algorithm

Support Vector Regression (SVR)

What is SVR:

A support vector machine (SVM) is used in Support Vector Regression (SVR), a supervised machine learning approach, to carry out regression tasks. SVR aims to fit the error inside a certain threshold in order to retain the greatest possible margin, in contrast to standard regression models that strive to minimise the total error.

How it Works:

SVR finds a hyperplane that maximises the margin while minimising the error by applying kernel functions to translate the input characteristics into a higher-dimensional space. It makes an effort to fit the data such that the difference between the expected and actual values falls within a predetermined range. The epsilon-insensitive loss function,

International Journal of Engineering Research and Science & Technology
https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472
ISSN 2319-5991 www.ijerst.com
Vol. 21, Issue 2, 2025

which establishes a margin of tolerance, and the support vectors are the two main parts of the procedure.

V. RESULTS AND DISCUSSION

Implementation and Description

views.py

1. **User Registration (register)**:
   - Manages user registration, which includes making sure the password and confirmation password match and verifying the originality of the email address and username.
   - Saves the user in the role they have chosen (admin or normal).
2. **Login (login_view)**:
   - Manages user authentication using a password and username. It verifies that the user is real and that the password is correct.
3. **Logout (logout_view)**:
   - Takes the user to the login page after logging them out.
4. **Data Upload (Upload_data)**:
   - o Manages CSV dataset file uploads. After reading the dataset, it separates it into training and testing sets after extracting the input (features) and output (target) variables. The prediction.html page displays the dataset.
5. **Machine Learning Model Functions**:
   - **DNN (dnn)**: Loads a pre-trained deep neural network (DNN) model or trains a new one if the model doesn't exist. It predicts on the test data and evaluates the model using performance metrics.
   - **SVR (SVr)**: Loads or trains a Support Vector Regressor (SVR) model, predicts on the test data, and evaluates the model.
   - **Bagging with Decision Trees (bagging_with_dt)**: Trains a Bagging Regressor model with Decision Trees as base estimators and evaluates the model.
6. **Prediction (prediction)**:
   - Allows uploading of test data, predicts using the trained Bagging Regressor model, and returns the results.

Setting.py

This is part of the Django settings file, which includes:

- **BASE_DIR**: Specifies the base directory of the project.
- **INSTALLED_APPS**: Lists the Django apps used in the project, including application (assumed to be the app containing the views and models).
- **DATABASES**: Configures the SQLite database for the project.
- **TEMPLATES**: Specifies the templates directory and configuration for rendering HTML templates.
- **PASSWORD_VALIDATORS**: Defines the password validation rules.

Suggestions for Improvement and Potential Issues:

1. **Security Enhancements**:
   - The SECRET_KEY in the settings.py is a static string in the code. It's recommended to store it in environment variables for security purposes (using django-environ or similar tools).
   - Debug should be set to False in production to avoid potential information leakage.
2. **Error Handling**:
   - The views.py script could benefit from more detailed error handling for file uploads and model predictions, especially for large files or invalid data formats.
3. **Model File Paths**:

International Journal of Engineering Research and Science & Technology
https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472
ISSN 2319-5991 www.ijerst.com
Vol. 21, Issue 2, 2025

- Ensure the model files (e.g., dnn_model.h5, svr_model.pkl) are stored in a secure location within the project, not accessible via the web server. Consider moving these to a subdirectory like /models and ensure the correct permissions are set.

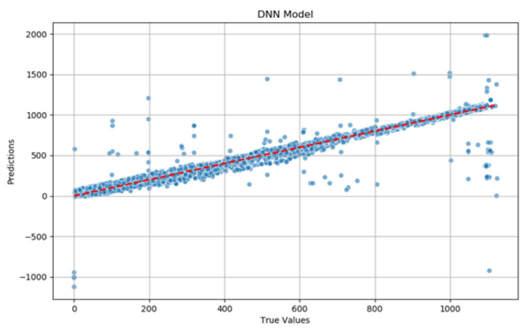
4. **File Handling and Deletion**:
    - It's good that uploaded files are deleted after processing, but ensure there's proper exception handling for file deletion failures (e.g., if the file is not found or cannot be removed).
5. **Code Optimization**:
    - The code for model loading, training, and prediction is similar across different algorithms. Consider creating a reusable function to reduce redundancy.

Dataset Description

- Cycle_Index: This is the battery's cycle index, which basically indicates how many cycles the battery has gone through when charging and draining.
- Discharge Time (s): The battery's discharge time (measured in seconds) across a full cycle.
- Deterioration 3.6-3.4V (s): The amount of time after discharge that the battery voltage remains between 3.6V and 3.4V.
- The highest voltage attained during the discharge phase is known as the maximum voltage discharge (V).
- The lowest voltage attained during the charging period is known as the "Min. Voltage Charg." (V).
- Time at 4.15V (s): The amount of time, measured in seconds, that the battery voltage remains at 4.15V when charging.
- Time constant current (s): The amount of time (in seconds) that the battery, whether in charge or discharge mode, receives a constant current.
- Charging time (s): The entire amount of time spent charging, expressed in seconds.
- Remaining usable Life, or RUL, is the battery's remaining usable life, usually indicating how long it will last before its performance deteriorates beyond a reasonable point.

RESULTS AND DESCRIPTION

	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
0	1.0	2595.30	1151.488500	3.670	3.211	5460.001000	6755.01	10777.82	1112
1	2.0	7408.64	1172.512500	4.246	3.220	5508.992000	6762.02	10500.35	1111
2	3.0	7393.76	1112.992000	4.249	3.224	5508.993000	6762.02	10420.38	1110
3	4.0	7385.50	1080.320667	4.250	3.225	5502.016000	6762.02	10322.81	1109
4	6.0	65022.75	29813.487000	4.290	3.398	5480.992000	53213.54	56699.65	1107

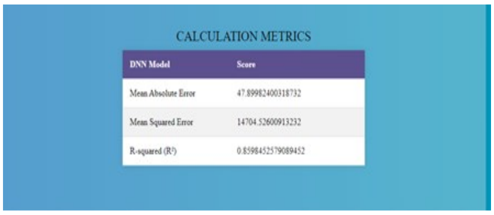


International Journal of Engineering Research and Science & Technology

https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472

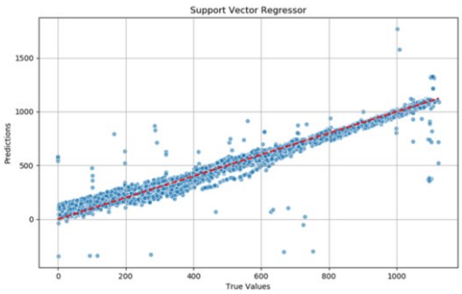
ISSN 2319-5991 www.ijerst.com

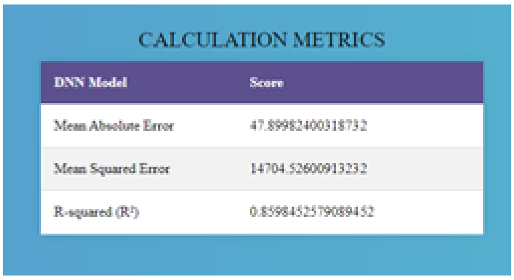
Vol. 21, Issue 2, 2025



CALCULATION METRICS

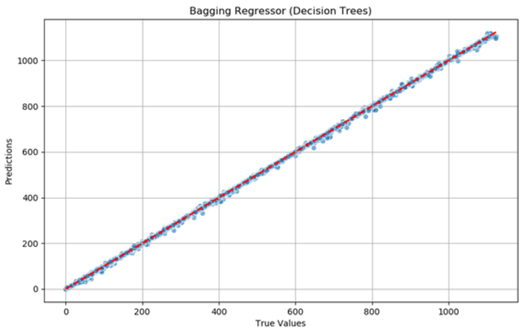
DNN Model	Score
Mean Absolute Error	47.89982400318732
Mean Squared Error	14704.52600913232
R-squared (R²)	0.8598452579089452

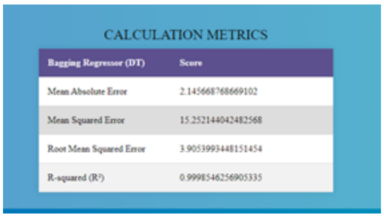




CALCULATION METRICS

DNN Model	Score
Mean Absolute Error	47.89982400318732
Mean Squared Error	14704.52600913232
R-squared (R²)	0.8598452579089452





CALCULATION METRICS

Bagging Regressor (DT)	Score
Mean Absolute Error	2.145668768669102
Mean Squared Error	15.252144042482568
Root Mean Squared Error	3.9053993448151454
R-squared (R²)	0.9998546256905335

VI. CONCLUSION AND FUTURE SCOPE

Conclusion:

The dataset provides valuable insights into battery performance and health over different charging and discharging cycles. By analyzing parameters like discharge time, voltage levels, and charging durations, we can model and predict the Remaining Useful Life (RUL) of batteries. This predictive capability can help in timely maintenance and replacements, ensuring optimal performance. The dataset is essential for researchers and engineers working on battery degradation, health monitoring systems, and predictive maintenance models, contributing to better battery management and longevity in applications like electric vehicles and energy storage systems.

Future Scope:

Future research could focus on improving prediction accuracy by integrating additional factors such as temperature, load, and environmental conditions that impact battery performance. Advanced machine learning algorithms, including deep learning models, could enhance the prediction of RUL, allowing for more precise health forecasting. Expanding the dataset with data from various battery chemistries and real-world usage scenarios could make the models more generalizable. Additionally, the integration of IoT systems for real-time battery monitoring and AI-based decision-making could revolutionize battery management in industries relying on critical energy storage.

REFERENCES

[1] Y. Gao, X. Zhang, B. Guo, C. Zhu, J. Wiedemann, L. Wang, and J. Cao, ''Health-aware multiobjective optimal charging strategy with coupled electrochemical-thermal-aging model for lithium-ion battery,'' IEEE Trans. Ind. Informat., vol. 16, no. 5, pp. 3417–3429, May 2020.

[2] J. Peng, Z. Zhou, J. Wang, D. Wu, and Y. Guo, ''Residual remaining useful life prediction method for lithium-ion batteries in satellite with incomplete healthy historical data,'' IEEE Access, vol. 7, pp. 127788–127799, 2019.

[3] H. Gabbar, A. Othman, and M. Abdussami, ''Review of battery management systems (BMS) development and industrial standards,'' Technologies, vol. 9, no. 2, p. 28, Apr. 2021.

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472
Vol. 21, Issue 2, 2025

[4] Y. Xing, E. W. M. Ma, K. L. Tsui, and M. Pecht, ''Battery management systems in electric and hybrid vehicles,'' Energies, vol. 4, no. 11, pp. 1840–1857, 2011.

[5] S. Jinlei, P. Lei, L. Ruihang, M. Qian, T. Chuanyu, and W. Tianru, ''Economic operation optimization for 2nd use batteries in battery energy storage systems,'' IEEE Access, vol. 7, pp. 41852–41859, 2019.

[6] K. Liu, X. Hu, Z. Wei, Y. Li, and Y. Jiang, ''Modified Gaussian process regression models for cyclic capacity prediction of lithium-ion batteries,'' IEEE Trans. Transport. Electrific., vol. 5, no. 4, pp. 1225–1236, Dec. 2019.

[7] C. She, Z. Wang, F. Sun, P. Liu, and L. Zhang, ''Battery aging assessment for real-world electric buses based on incremental capacity analysis and radial basis function neural network,'' IEEE Trans. Ind. Informat., vol. 16, no. 5, pp. 3345–3354, May 2020.

[8] B. Xu, J. Zhao, T. Zheng, E. Litvinov, and D. S. Kirschen, ''Factoring the cycle aging cost of batteries participating in electricity markets,'' IEEE Trans. Power Syst., vol. 33, no. 2, pp. 2248–2259, Mar. 2018. [9] N. Qi, K. Dai, F. Yi, X. Wang, Z. You, and J. Zhao, ''An adaptive energy management strategy to extend battery lifetime of solar powered wireless sensor nodes,'' IEEE Access, vol. 7, pp. 88289–88300, 2019.

[10] C. Zhang, Y. Wang, Y. Gao, F. Wang, B. Mu, and W. Zhang, ''Accelerated fading recognition for lithium-ion batteries with nickel-cobalt-manganese cathode using quantile regression method,'' Appl. Energy, vol. 256, Dec. 2019, Art. no. 113841.

[11] H. Liu, F. Chen, Y. Tong, Z. Wang, X. Yu, and R. Huang, ''Impacts of driving conditions on EV battery pack life cycle,'' World Electr. Vehicle J., vol. 11, no. 1, p. 17, Feb. 2020.

[12] M. Corno and G. Pozzato, ''Active adaptive battery aging management for electric vehicles,'' IEEE Trans. Veh. Technol., vol. 69, no. 1, pp. 258–269, Jan. 2020.

[13] K. Liu, Y. Li, X. Hu, M. Lucu, and W. D. Widanage, ''Gaussian process regression with automatic relevance determination kernel for calendar aging prediction of lithium-ion batteries,'' IEEE Trans. Ind. Informat., vol. 16, no. 6, pp. 3767–3777, Jun. 2020.

[14] J. Ma, S. Xu, P. Shang, Y. Ding, W. Qin, Y. Cheng, C. Lu, Y. Su, J. Chong, H. Jin, and Y. Lin, ''Cycle life test optimization for different Li-ion power battery formulations using a hybrid remaining-useful-life prediction method,'' Appl. Energy, vol. 262, Mar. 2020, Art. no. 114490.

[15] M. Behdad Jamshidi, M. Jamshidi, and S. Rostami, ''An intelligent approach for nonlinear system identification of a Li-ion battery,'' in Proc. IEEE 2nd Int. Conf. Autom. Control Intell. Syst. (I2CACIS), Kota Kinabalu, Malaysia, Oct. 2017, pp. 98–103.

[16] M. B. Jamshidi, N. Alibeigi, A. Lalbakhsh, and S. Roshani, ''An ANFIS approach to modeling a small satellite power source of NASA,'' in Proc. IEEE 16th Int. Conf. Netw., Sens. Control (ICNSC), Banff, AB, Canada, May 2019, pp. 459–464.

[17] Y. Shi, B. Xu, Y. Tan, D. Kirschen, and B. Zhang, ''Optimal battery control under cycle aging mechanisms in pay for performance settings,'' IEEE Trans. Autom. Control, vol. 64, no. 6, pp. 2324–2339, Jun. 2019.

[18] M. B. Jamshidi and S. Rostami, ''A dynamic artificial neural network approach to estimate thermal behaviors of Li-ion batteries,'' in Proc. IEEE 2nd Int. Conf. Autom. Control Intell. Syst. (I2CACIS), vol. 7, Kota Kinabalu, Malaysia, Oct. 2017, pp. 116–121.

[19] Y. Wu, W. Li, Y. Wang, and K. Zhang, ''Remaining useful life prediction of lithium-ion batteries using neural network and bat-based particle filter,'' IEEE Access, vol. 7, pp. 54843–54854, 2019.

[20] A. El Mejdoubi, H. Chaoui, H. Gualous, P. Van Den Bossche, N. Omar, and J. Van Mierlo, ''Lithium-ion batteries health

International Journal of Engineering Research and Science & Technology
ISSN 2319-5991 www.ijerst.com
https://doi.org/10.62643/ijerst.2025.v21.i2.pp462-472
Vol. 21, Issue 2, 2025

prognosis considering aging conditions,'' IEEE Trans. Power Electron., vol. 34, no. 7, pp. 6834–6844, Jul. 2019.