International Journal of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

AN INTELLIGENT MACHINE LEARNING MODEL FOR ELECTRICVEHICLES (EVS) BATTERY PERFORMANCE EVALUATION

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Abstract

Electric cars (EVs) are becoming increasingly popular due to their benefits for the environment and low operating costs. Nevertheless, the limited battery life is still one of the major issues with EVs. The present research introduces a cutting-edge and strong machine learning-based system that accurately forecasts the Remaining Useful Life (RUL) of lithium-ion batteries very effectively through the use of a time-series dataset consisting of 14 battery cells obtained from Kaggle. The research method includes thorough data preprocessing like error correction, irrelevant feature removal, Standard Scaler normalization, and outlier treatment by the IQR method. SMOTE was used to tackle the problem of class imbalance. Various models of machine learning, such as XGBoost and Bagging Regressor, were counted among those that were subjected to performance evaluation through the metrics R^2, RMSE, MSE, and MAE. The experimental findings indicate that XGBoost beats the other models by getting the highest R^2 (99.7) and the lowest error rates, which are synonymous with prediction accuracy and robustness. The reliability of the model is shown by its residual and distribution plots, while its comparison with other existing methods is a newly developed performance criterion of a very high level. The introduced framework is a great resource for battery diagnostics and predictive maintenance improvements in EVs.

Keywords: Electric Vehicles (EVs), Lithium-Ion Batteries, Machine Learning, Battery Degradation, Battery Diagnostics.

I. INTRODUCTION

Electrochemical battery cell-based energy storage systems have been in use since the middle of the 1800s. Over the past century, accumulator battery technologies have steadily advanced, new cell types have emerged, and energy density, service life, and operational dependability have all increased. The ease of scaling [1], or the ability to include a certain number of battery cells into a battery pack with the necessary characteristics (capacity, power, voltage), is a key benefit of electrochemical accumulator batteries. One of the areas of the energy sector growing the fastest now is battery production. The most prevalent kind of battery cell is Lithium-ion (Li-ion).

Li-ion batteries, which have a high energy density, no memory effect, a long lifespan, and adaptability in charging and discharging, are the most common kind used in electric vehicles (EVs). Notwithstanding these advantages, the automotive industry still faces challenges from erratic weather patterns and increasing air pollution from vehicle emissions., and supply chain uncertainty for renewable energy. The energy found in EV batteries has the ability to resolve environmental concerns and uncertainties. The development and widespread use of EVs with greater reliability, safety, and range is crucial to the decarbonization of the transportation industry. Nevertheless, employing Li-ion batteries has disadvantages, such as capacity loss, environmental issues, and end-of-life challenges. Energy saving and environmental preservation have become global priorities. The automotive industry has a significant impact on greenhouse gas (GHG) emissions and energy consumption worldwide. Governments all around the globe have thus devised policies to reduce the transportation sector's GHG emissions. EVs using electric propulsion are becoming a more sustainable mode of transportation [2]. As efficiency and performance might be compromised by a single energy-storage system, HESS is being investigated to segregate power and energy services.

The most common form of EVs commercially is battery EVs (BEVs). They are based on electric motors and rechargeable battery packs. The importance of monitoring battery thermal conditions during operation is reflected in the inclusion of ML and DL of LIB lifetime and degradation models in offering more tools that can be used in solving the intricate chemical and physical processes involved. Varied methodological designs have varying strengths on a particular application, data availability and operational limitations. The main aim of ML is to handle a set of data to generate predictive models. The maximization of accuracy is done using optimization algorithms during the process of model training. The principle of these models is that the parameters are adjusted to fit the data with complex relationships. Predictive models are applied in the EV domain to estimate the energy requirement of the vehicle, and predict the battery SoC in real time as the vehicle travels along a predetermined route.

A. Motivation and Contribution of the Study

Electric cars rely heavily on lithium-ion batteries, yet they lose their competence and become expensively priced in real-life circumstances. The classical models cannot capture the complex behaviour that formed the demand for data-driven ML techniques to provide accurate battery health and RUL predictions. This is due to the fact that the correct estimation of the RUL allows real-time monitoring, predictive maintenance, and the move towards sustainable and efficient electric mobility is also preferable.

The following are this study's main contributions:

- Utilized the RUL data set of Kaggle to predict the EV batteries accurately.
- Applied a large variety of preprocessing procedures that involved the deletion of errors, feature selection, the cleansing of outliers against IQR, and data normalization to enhance data quality.

International Journal of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

- The imbalance was addressed with a SMOTE to generate synthetic data to counter the imbalance, allowing generalizability of the model restricting biased predictions.
- Implemented ML techniques namely, Extreme Gradient Boosting (XGBoost) and Bagging Regressor.
- To evaluate and compare the different ML models, especially XGBoost and Bagging Regressor, the evaluation was conducted according to the standard performance measures (R^2, RMSE, MSE, MAE) of the two models.

B. Novelty and Justification of the Study

The originality of the current research is the combination of a robust pre-processing pipeline using advanced ML techniques to accurately forecast lithium-ion batteries' RUL. The present study takes a different route whereby IQR-based outlier removal, SMOTE for data balancing, and feature-focused normalization are done on it. The integration of XGBoost is another point that highlights the accuracy of predictions as higher than that of other benchmark models. Consequently, it can be a practical approach for diagnosing batteries, with remarkably widespread application, less susceptibility to noise, and the possibility of assessing the importance of features. The proposed method significantly improves RUL identification accuracy and also results in improved predictive maintenance schedules for battery systems in EVs.

C. Structure of the paper

The paper is organised as follows: Section II reviews the relevant literature on the Performance Evaluation of EV Batteries, Section III outlines the methodology, Section IV presents the results and model comparisons, and Section V concludes with observations and recommendations for future research.

II. LITERATURE REVIEW

The studies about EV battery performance reviewed in this section highlight the usage of ML and optimization techniques for health estimation, SoC prediction, energy management, and RUL forecasting, while the key themes are data-driven modelling, predictive maintenance, real-time monitoring, and BMS integration.

Khawaja et al. (2023) The techniques used include SVM regressors, gradient boost, light-GBM, RF, linear, and XGB. Compared with the other models employed in this study, the discharge forecast using RF performs considerably better at a slight loss in accuracy. The RF regressor obtains 0.0035, 0.0013, and 0.0097 for mean and MAE and RMSE, respectively, while having the highest R2-score of 0.999[3].

Tran et al. (2022) analyze the effectiveness of four distinct ML models for forecasting the electrical (voltage) and thermal (temperature) characteristics of Li-ion battery cells. A 25-ohm prismatic Li-ion battery cell was cycled at three different ambient temperatures while maintaining a consistent current profile. Additionally, the battery's surface temperature and voltage were monitored. Four ML regression models were created using the scikit-learn Python module. By contrasting them with the experimental data, the models LR, KNN, RF, and DT—were verified. The R2 metric was used to report and compare the results of their performance. The best model in this case study was determined to be the DT-based model, which has an R2 score of 0.99[4].

Yalçın, Panchal and Herdem (2022) AI techniques, LR, MLR, DT, RF, SVM, ANN, LSTM, and simple CNN, are compared with the recommended approaches. The performance findings provide compelling proof of the superiority of the suggested CNN-ABC method. When the ABC is applied to the suggested CNN architecture, the suggested approach produces RMSE and R2 of 1.38% and 99.72% for HGR estimate and 3.55% and 99.82% for voltage data estimation, respectively[5].

Chandran et al. (2021) show the SoC estimation using six ML algorithms for lithium-ion battery systems used in EV applications. The methods used include ANN, LR, GPR, ensemble bagging (EBa), ensemble boosting (EBo), and SVM. The battery's performance parameter is optimized using an error analysis of the model. The contestation of performative indices comes next. ANN and GPR are shown to be the most effective methods based on MSE and RMSE of (0.0004, 0.00170) and (0.023, 0.04118), respectively[6].

Babaeiyazdi, Rezaei-Zare and Shokrzadeh (2021) models aim to learn from input features and establish a corresponding relationship with SOC. The findings show that the GPR model's accuracy was below 3.8%. Considering onboard EIS data, this method may be successfully included in the battery management system for accurate SOC measurements of Li-ion batteries and ensure the proper and efficient operation of battery-powered EV[7].

Yavasoglu, Tetik and Ozcan (2020) Convex optimization of complex systems can be challenging since there are too many factors to consider and not all systems can be linearized. To tackle the problem of multi-objective energy management, an ML technique based on NN is suggested. Convex optimization outputs are utilized to train the suggested NN model, and simulation results demonstrate that the optimized problem is solved by the trained NN model within 92.5% of the convex optimization one[8].

The comparative analysis of background study based on their Methodology, Dataset/Environment, Problem Addressed, Performance and Future Work/Limitation is provided in Table I

International Journal of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

TABLE I. REVIEW OF LITERATURE ON PERFORMANCE EVALUATION OF ELECTRIC VEHICLE'S BATTERY

Author	Methodology	Environment / Dataset	Problem Addressed	Performance	Future Work / Limitation
Khawaja et al. (2023)	Linear Regression, Random Forest, Gradient Boost, LightGBM, XGBoost, SVM Regressors	Battery discharge prediction dataset	Predicting discharge with high accuracy	Random Forest achieved R^2 = 0.999, MAE = 0.0035 & 0.0013, RMSE = 0.0097	Can explore hybrid and deep learning models for further accuracy
Tran et al. (2022)	Linear Regression, KNN, Random Forest, Decision Tree	Prismatic Li-ion battery (25Ah) cycled under 3 ambient temperatures	Thermal (temperature) and electrical (voltage) prediction	Decision Tree achieved R^2 = 0.99	Requires real-time implementation and scalability testing
Yalçın, Panchal & Herdem (2022)	CNN-ABC in contrast to LR, MLR, DT, RF, SVM, ANN, LSTM, and Basic CNN	HGR and voltage datasets	Battery parameter estimation	CNN-ABC achieved RMSE = 1.38%, R^2 = 99.72% (HGR), and R^2 = 99.82% (voltage)	Complexity of model and high computation cost
Chandran et al. (2021)	Ensemble Bagging, Ensemble Boosting, ANN, SVM, LR, and GPR	SoC estimation dataset	Improving SoC prediction for EV batteries	GPR (MSE = 0.023, RMSE = 0.04118), ANN (MSE = 0.0004, RMSE = 0.00170)	Needs integration with BMS and real-time testing
Babaeiyazdi et al. (2021)	Gaussian Process Regression (GPR)	Onboard EIS measurements	SOC prediction from input features	Error < 3.8%	Deployment challenges within BMS systems
Yavasoglu et al. (2020)	Neural Network trained on convex optimization outputs	Convex optimization-based simulation	Multi-objective energy management	Trained NN achieved 92.5% performance of ideal optimization	The model may not generalize to real-time complex systems

III. METHODOLOGY

The proposed methodology uses a Kaggle RUL (Remaining Useful Life) dataset along with the application of a data pre-processing pipeline that takes in error removal, irrelevant column removal, outlier treatment through IQR, and so on systematically. After that, the data is standardized via Standard Scaler and subsequently SMOTE is used for balancing. Following the 80:20 splitting of the dataset into training and testing sets, many ML methods, including XGBoost, Bagging Regressor, and RF have been trained. The evaluation of model performance is done by using metrics like R^2, RMSE, MSE, and MAE, and the results are displayed in order to determine the best model for RUL prediction. Figure 1 shows the flowchart of the methodology explained in the section.

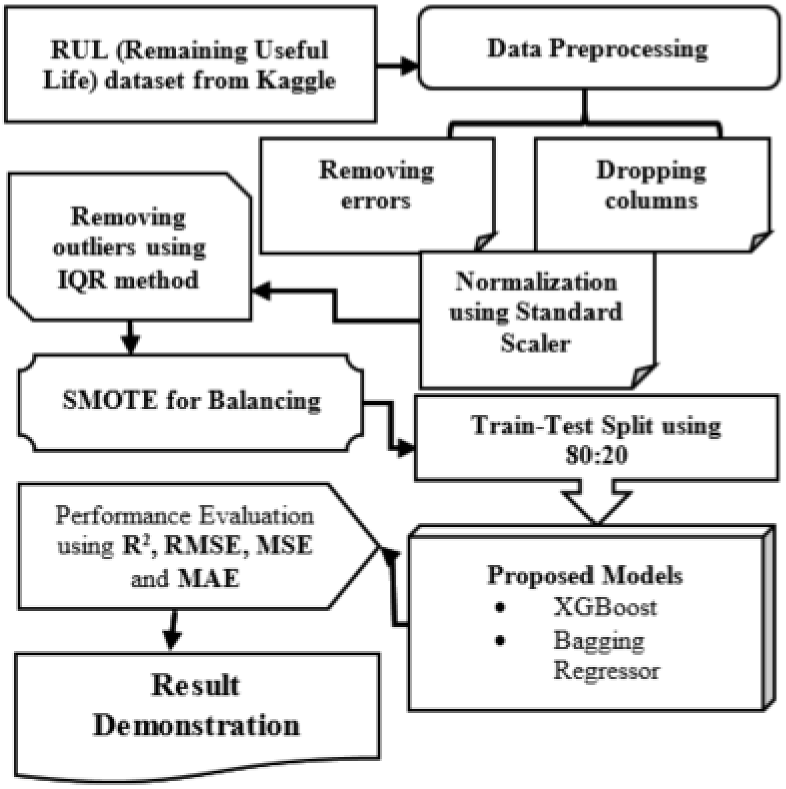

Fig. 1. Flowchart Representation of the Performance Evaluation of an Electric Vehicle's Battery

Each step of the flowchart is explained in the section below:

A. Data Collection

The study used the RUL dataset taken from Kaggle . The dataset is a time-series-based summary of 14-lithium lithium-ion battery cells. Particular row implies one charge/discharge of a cell encompassing multiple features like discharge time, time at constant current, time at 4.15 V, total cycle time and the target variable which is specified as the number of cycles. The data set is 14 folds, each 1,000+ cycles in length. The EDA of the dataset is presented below:

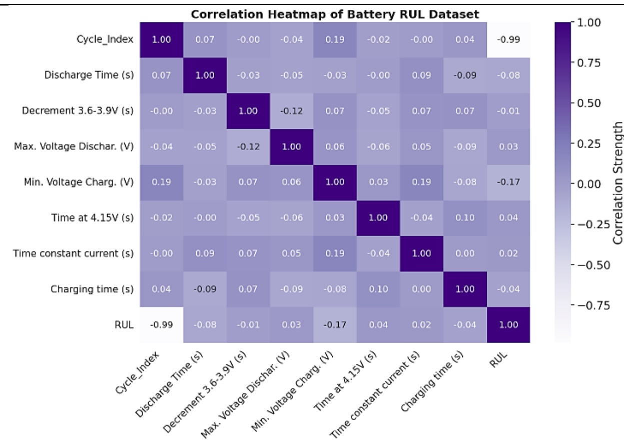

Fig. 2. Correlation Heatmap of Battery RUL Dataset

The heatmap of correlations within the Battery RUL dataset is illustration in Figure 2, depicting the relationships between various features and RUL. The negative correlation between Cycle_Index and RUL is very strong, implying that the battery quality deteriorates as the number of cycles increases. By contrast, other features show weak correlations, indicating they have a limited individual impact on battery degradation.

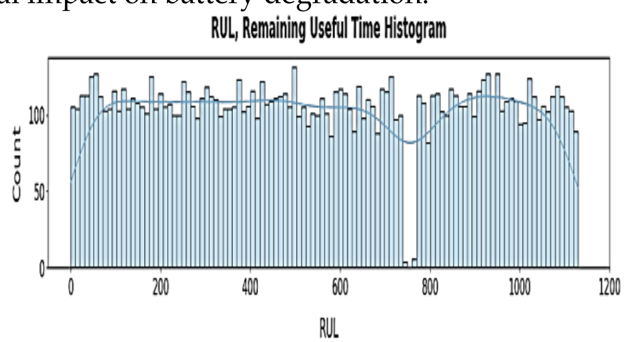

Fig. 3. RUL Remaining Useful Time Histogram

Figure 3 illustrates the RUL values and their distribution within the dataset. The RUL values seem to be distributed approximately uniformly, which means that the data has recorded a variety of battery lives. The evenness of the distribution is a good factor for model training since it allows for enough representation from both ends of the RUL spectrum, the lower and the higher ones.

B. Data Preprocessing

Several crucial procedures were completed throughout the stage of data processing that prepares the dataset for modelling and analysis. The pre-processing steps involved in this study are defined below:

International Journal of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

- **Removing errors:** The data was cleaned by removing the inconsistencies and errors and the relevant features were selected and engineered. Ensure that you do sanity checks while handling missing values and identifying identical values.
- **Dropping columns:** Irrelevant columns were removed from the dataset and only the key features like cycle index, discharge and charging times, voltage variations, and RUL that effectively represented battery behavior and degradation patterns were kept to make accurate Remaining Useful Life prediction easier.
- **Normalization using Standard Scaler:** Normalization may be considered as a scaling method that alters the extensive feature range into a normal one. Usually, this new range is from zero to one. The Equation (1) for normalization used in this study is given below:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where Xis the beginning value of a feature, X_min denotes its minimum value, and X_maxDenotes its maximum value.

C. Removing Outliers using IQR Method

The mean and standard deviation may be significantly impacted by outliers, which are the most common statistical measures, and this could result in the data being less representative of the usual behavior. Predictive models can be improved by eliminating outliers, which guarantees that the RUL estimations given by these models are more accurate. In this research the outliers were removed using the IQR method. It calculates IQR (interquartile range) for the observed time series RSS, which is the difference between the 75th and 25th percentile. RSS observations that are outside of the range defined by the IQR are considered outliers. IQR defines an outlier to be an observation that is outside the range, for some constant k. The value of Q_3-Q_1It is referred to as IQR.

$$[Q\_1 - k(Q_3 - Q_1\ ), Q_3 + k(Q_3 - Q_1)]$$

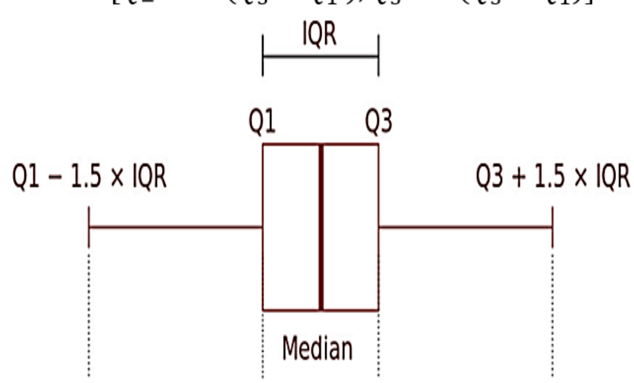

Fig. 4. Projecting the interquartile range (IQR) on a density with a normal distribution

An ordered set of items is divided into quartiles to provide the data variability metric shown in Figure 4.

D. SMOTE for Balancing

Synthetic Minority Oversampling approach (SMOTE) is another resampling approach used to balance datasets with a severely uneven ratio. Its objective is to increase the quantity of minority class samples by creating artificial minority class samples. The multiplication strategy differed from the synthetic creation of new samples in order to prevent the overfitting problem. The main idea behind SMOTE is to interpolate between samples of this class that are close to one another in order to generate fresh minority class data samples. As a result, SMOTE increases the amount of minority class examples in an imbalanced dataset, improving the classifier's generalizability.

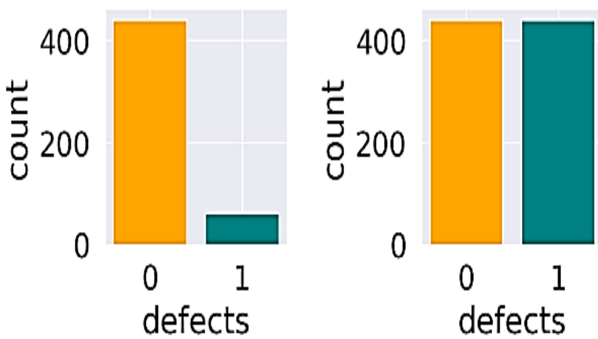

Fig. 5. Imbalanced and Balanced Graph of the Dataset

Figure 5 presents data for defective and non-defective sample counts in comparison. The very first graph reveals an extreme class imbalance, whereas the subsequent one depicts a balanced distribution due to the application of resampling techniques for the purpose of enhancing model training.

E. Data Splitting

Data splitting into training and testing sets to evaluate the efficacy of the model. The RUL dataset was used to build an 80:20 training and test set.

F. Proposed Machine Learning Models

This section outlines the proposed ML approaches employed in evaluating the battery performance of the EVs.

- **XGBoost:** XGBoost is a powerful regression and classification method. XGBoost continuously creates new DT based on the GB architecture in order to fit a number with several residual iterations and increase the learners' effectiveness. Rather than using GB, XGBoost compares the loss function using a Taylor expansion. The model compromises the bias-variance trade-off effectively and allows achieving the required accuracy with fewer decision trees. This is how XGBoost is explained. To accurately estimate a battery's RUL, the retrieved attributes are mapped together using XGBoost. The main methodology of the central idea behind XGBoost is to train some decision trees to predictive a previously trained model’s residual. With each repeat, the expected value becomes more precise.

International Journal of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

Different leaf nodes are given samples based on how each tree is constructed. A tree's predictive score is the total of its leaf node weights. The total of each tree's score may be used to determine the data set's anticipated value. As in Equation (2), let's investigate a sample set of n samples for the features:

$$D = (X_z, y_z) \rightarrow z = 1,2,3, \dots . N \qquad (2)$$

where D: dataset comprising input and output variables; X_z: feature vector; y_z: target value and z: Index of each sample.

- **Bagging Regressor:** Bagging is an integrated learning method that, by combining many sub-models, lowers the generalization error and enhances prediction accuracy and stability. In contrast to bagging, boosting reduces variation and bias in the classification problem by basing the classifiers' votes solely on their relative accuracy.

G. Performance Matrix

A number of error measures, including as MSE, R2 (coefficient of determination), MAE, and RMSE, were computed for using the test dataset, each model is trained and tested.

R2 indicates the degree of correlation between the predicted and actual values. These values range from -1 to 1, where a legitimate negative linear relation is represented by −1, no relation by 0, and a proper positive linear relation by 1. MAE is the average of the difference between the actual and expected values. RMSE is the R2 of the difference between actual and anticipated values, much like MAE. Consequently, the emphasis is on bigger errors rather than smaller ones. MSE emphasises making fewer errors by punishing them more severely. It accomplishes this by figuring out the mean of the squared differences between the expected and actual values. The Equations (3)-(6) represents the mathematical formulation of the parameters:

$$R^2 = 1 - \frac{\Sigma(y_i - y_p)^2}{\Sigma(y_i - \overline{y_i})^2} \qquad (3)$$

$$MAE = \frac{|(y_i - y_p)|}{n} \qquad (4)$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_i - \widehat{y_i})^2 \qquad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_i - \widetilde{E_i})^2} \qquad (6)$$

IV. RESULTS & DISCUSSION

The experiment uses an Intel Core i5 8th-generation CPU operating at 2.30GHz with 8GB RAM. Spyder and Jupyter Notebook, which are installed in the Anaconda Python 3.7 environment, are

International Journal of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

the IDEs utilized. Table II presents a comparison between XGBoost and LightGBM in terms of their performance for the assessment of EV batteries. It is clear from the results that XGBoost is still the one that takes the lead by a small margin, since it realizes R^2 of 99.7 which is higher than LightGBM's 99.5, therefore the former is more accurate. Besides, the XGBoost model has lower error values in all metrics, RMSE (15.6 vs. 20.4), MSE (245.9 vs. 416.9), and MAE (8.1 vs. 12.5), which correspond to its predictions being more precise. The assessment indicates that XGBoost is the winner over LightGBM in terms of efficacy for the electric vehicle battery modeling.

TABLE II. EVALUATION OF XGBOOST FOR PERFORMANCE EVALUATION OF ELECTRIC VEHICLE'S BATTERY

Metrics	XGBoost	LightGBM
R2	99.7	99.5
RMSE	15.6	20.4
MSE	245.9	416.9
MAE	8.1	12.5

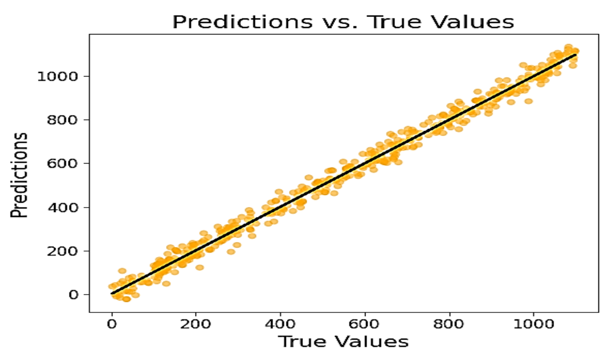

Fig. 6. Predicted vs. Actual Plot

Figure 6, Real vs. Forecast Plot visually contrasts the batteries' actual and expected values with the RUL values that the XGBoost algorithm predicts.

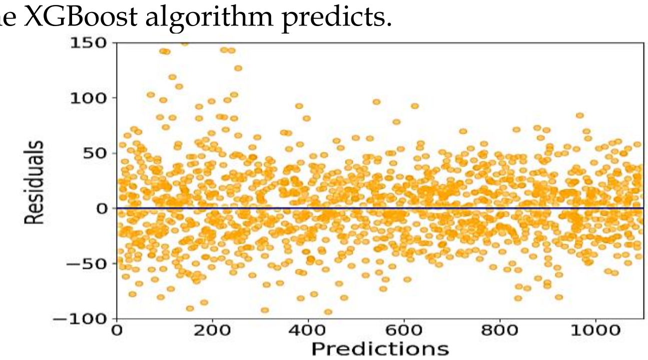

Fig. 7. Residual Plot

International Journal of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

The residual plot in Figure 7 displays the discrepancies between the anticipated and actual RUL values. In essence, the magnitudes and orientations of errors are displayed by the vertical distances between data points and the horizontal reference line (usually at y = 0).

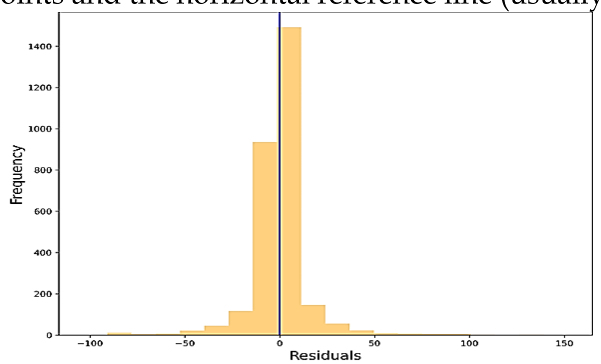

Fig. 8. Residual Histogram

Figure 8 displays the residual histogram of the XGBoost residual prediction model. This histogram shows how the prediction mistakes are distributed, giving information on how frequently and widely they occur. The model's mistakes would be randomly distributed and unbiased if they were represented by a bell-shaped curve with a zero center.

A. Comparative Analysis

Table III summarizes a comparison of several ML models for assessing the performance of electric car batteries. Among the studies cited, the SVM model won the race with the highest accuracy, yielding an R^2 value of 97.3, while AE+DNN and Ridge Regressor came next with respective scores of 93.34 and 92.8. Meanwhile, the XGBoost model proposed has overtaken all others by getting the largest R^2 score of 99.7, thus substantiating its prediction power and stability. This is seen as the proof of XGBoost's capability in precise battery performance modeling right up to the state-of-the-art methods present in the study.

TABLE III. COMPARATIVE ANALYSIS ON PERFORMANCE EVALUATION OF ELECTRIC VEHICLE'S BATTERY

Reference	Models	R2
[9]	AE+DNN	93.34
[10]	SVM	97.3
[11]	Ridge Regressor	92.8
Proposed	XGBoost	99.7

The suggested XGBoost model is a powerful option for electric vehicle battery performance assessment, as it has many advantages. It does a great job at dealing with complex and nonlinear data relationships while being resistant to noise, thus it is perfect for predicting battery degradation. In addition, the model involves regularization, which is a method to regulate overfitting and enhance the model's performance under various battery conditions. XGBoost, in addition, allows us to conduct an analysis of feature importance that consequently expounds on what influences the state of the battery. In conclusion, one can explain the reason why the model is practically applied in battery diagnostics and predictive maintenance is the fact that it enables obtaining consistently high-quality predictions.

V. CONCLUSION & FUTURE WORK

The study was successful because it showed that ML can accurately predict lithium-ion batteries' RUL, which is an extremely significant aspect of enhancing the reliability and sustainability of EVs. This study is based on and employs a well-structured dataset and sophisticated modeling methods and has concluded that XGBoost is an excellent model that represents highly complex battery degradation trends. The model is among the best in accuracy and consistency when contrasted with alternative techniques. The results suggest that the model works in terms of practical applications, such as predictive maintenance and battery diagnosis in real-world scenarios. The investigation not only provides a good basis for the approval of data-driven techniques in energy storage systems but also stimulates advanced studies in the fields of battery monitoring, model deployment, and integration with IoT-enabled battery management systems.

Real-time prediction of remaining useful life (RUL) through online learning and adaptive models can be a future research topic. Furthermore, temperature and charging behavior could also be considered in order to enhance the accuracy level. Moreover, deep learning architectures and physics-informed models could be jointly employed to make the monitoring of electric vehicle batteries more robust and scalable in terms of large-scale applications.

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