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Forecasting the Battery RUL of EV Using ML

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A B S T R A C T

Electric vehicles (EVs) are becoming more and more popular because of their beneficial environmental effects and low operating costs. However, one of the main problems with EVs is their short battery life. When a battery is used and recharged repeatedly over time, a natural process of battery degeneration takes place. But a number of factors, such as high temperatures, rapid charging, and deep discharge, can hasten the deterioration of batteries. These components may be used to forecast the battery life of EVs using machine learning (ML), together with other relevant data such as driving patterns, vehicle type, and weather conditions. To learn how these factors affect battery degeneration, ML models can be trained using historical EV data. The ML models can be used to predict the battery life of devices after being trained. In this paper we tested with XG Boost, KNN, Random Forest, Decision tree and Naïve Bayes algorithms.

Keywords: *Remaining usable life; battery; Machine Learning; XG Boost; KNN; Random Forest; Decision tree; Naïve Bayes.*

1. Introduction

Electric vehicles (EVs) typically use lithium-ion (Li-ion) batteries due to their high energy density, lack of memory effect, long lifespan, and ability to charge and discharge multiple times. One of the main causes of changing weather conditions and poor health is the sharp increase in air pollution from vehicle emissions. Additionally, weather-related risks and supply chain issues also affect renewable energy sources, including solar, wind and biofuels. The energy provided by electric cars, stored in batteries, is an attractive way to partially eliminate pollutants and uncertainties. Decarbonization of the transportation industry depends on the creation and adoption of advanced electric vehicles (EVs) with greater range, safety and reliability. However, the use of lithium-ion batteries is significantly hindered by capacity degradation over time and use, environmental degradation issues, and end-of-life reuse. After an average of 6.5 years of regular operation, the battery capacity of an electric vehicle will decrease by about 10%. Finding a reliable way to predict remaining life (RUL) and monitor capacity degradation is a difficult task. In actual use, Li-ion batteries gradually lose capacity by going through many charge and discharge cycles until they reach end of life (EOL). The standard definition of shelf life is 70% or 80% of rated capacity. Battery capacity decreases more quickly after use ends, which can affect or even damage battery performance. How to predict future capacity and RUL, as well as how to communicate the level of uncertainty around the predicted value, are among the topics covered in battery management systems (BMS). With this knowledge, electric vehicle owners can make informed decisions to avoid battery failure. Because the trajectory of battery capacity degradation is complex and extremely non-linear, it is difficult to make accurate predictions of capacity and RUL. There are many benefits to using ML to predict electric vehicle battery life. It can help electric vehicle owners plan their trips better and avoid battery drain. Additionally, it could help electric vehicle manufacturers create longer-lasting batteries and develop charging techniques that reduce battery damage. In this study, ML Random-forest, Decision Tree, XG boost, KNN and Naive Bayes algorithms are used to predict the battery life of electric vehicles. Using machine learning to predict battery life raises many ethical questions. Some of the most important are accuracy and fairness, objectivity and accountability.

The quality of the data used to train the ML model depends on that data. The model will provide biased or inaccurate predictions if the data is skewed or wrong. It is important to properly evaluate data quality before using it to train ML models and take precautions to eliminate any potential bias. Accountability and transparency:

ML models can be complex and difficult to understand. It is essential to be open about the inner workings of models and take responsibility for their predictions. In this regard, battery performance is established by calculating the remaining useful life (RUL). By identifying factors that will promote and improve the efficiency of electric vehicle upgrades, it also contributes to the testing and development of various electric vehicle upgrades. This process involves a number of complex and non-linear factors. Engineering problems in this field (non-linearity and complexity) can be optimized and modeled using machine learning (ML) approaches. Scalability and time constraints associated with battery degradation are overcome with ML methods, providing a non-invasive solution with high precision and little processing. This article provides an objective and in-depth assessment of these difficulties, based on recent research. RUL estimates are discussed thoroughly along with examples of how they can be used. Additionally, several ML methods for RUL evaluation are being extensively and separately studied. Finally, an application-specific review is provided, highlighting the benefits in efficiency and accuracy. An important alternative to provide sustainable and environmentally friendly solutions is the electrification of transport infrastructure. This is

because it addresses both the growing demand for environmentally friendly energy sources and the increasing transportation costs. This is important for the pursuit of sustainable development on a global scale. Electric vehicles will help dominate the low-emissions industry, whether they are battery-powered hybrid electric vehicles (HEVs) or electric vehicles that run on both fossil fuels and batteries. HEVs and EVs can run on both gasoline and conventional batteries.

The main causes of active material loss among these are electrode particle cracking, binder degradation, graphite exfoliation, and electrical contact degradation caused by accumulator corrosion. The main sources of lithium depletion include electrolyte breakdown, degradation of solid electrolyte (SI) interphase films, and lithium plating. It's important to note that these material degradation processes are intimately related to the materials themselves. Because graphite has a negative work function, its anode's operating voltage is lower than the electrochemical window of most electrolytes, causing a SE interphase layer to form. The capacity of LT oxide, however, stays within the range of electrochemical electrolyte, therefore SE interphase film development would not take place in the anode constructed of this material. Changes in the volume of a cathode composed of lithium iron are another illustration of this as they cause less structural deformation than a cathode formed of lithium manganese oxides. The deterioration processes differ greatly based on the operating circumstances and design of the battery, in addition to changes in the materials. For instance, the chance of lithium plating occurring during fast charging is far higher than it is during battery depletion. Smaller cathode elements lower pressures in the battery's design, which in turn results in fewer particle breakage. However, due to the cathode's large specific surface area, this also increases cathode material dissolution. It is getting harder and harder to predict with accuracy how long a battery will last due to the intricacy of the mechanism by which batteries decay. To ensure constant functioning, time maintenance, as well as future applications including battery reuse, this is crucial in the case of temperature management of battery packs.

1.1 Objectives of the Study

RUL's exact forecast is still difficult. Researchers in this discipline have employed a variety of strategies, including modern strategies like RSM for optimization. But more current techniques have been used, including gaussian process regression enhanced regression trees, XGBoost, Navi Bayes, Random Forest, and decision trees. Additionally, techniques for refining the model's training, such as Bayesian optimization, random and grid search, and unscented Kalman filters, are used. The review studies that have been published in recent years do not, however, give thorough information on these methods. Consequently, the goal of the current study is to give the most recent information on machine learning (ML), hyperparameter optimization, and parametric optimization in the context of remailing meaningful life modeling. The energy storage system, also known as the battery, is the most important component of an electric vehicle. The first electric car became accessible to the public thanks to the development of rechargeable lead-acid batteries in the early 19th century. Electric cars then grew rapidly in popularity until the first decades of the century. 20th century. At that time, the number of electric cars sold worldwide was more than double that of cars powered by fossil fuels, setting a record that has never been surpassed. Today, lithium-ion (Li-ion) batteries are needed to make electric vehicles a reality. These batteries are designed to operate modern electric vehicles modified to meet human needs. This number is expected to decrease as electric cars become more popular in road transport. While this may not be the only factor in reviving a centuries-old idea that has been dormant for a very long time, this time it is a commercially viable product that is capable of competing. compete with cars that run on fossil fuels. Electric vehicles (EVs) are quieter, require less labor to operate and use less fuel than conventional cars. This is a big advantage, especially if oil prices continue to rise. The technology developed so far has the potential to be used in urban transportation to solve problems such as traffic congestion and affordable public transport. It produces very little waste and uses no stored energy. Energy transportation and storage sector has been archived. The energy transportation and storage sector frequently use Li-ion batteries. They must be handled and monitored properly as they are one of the most expensive components and play a vital role. Longer battery life is essential for the infrastructure supporting renewable energy sources associated with smart grids, as well as for the economic sustainability of electric vehicles (EVs). One of the biggest and most difficult problems to solve is battery wear and tear during use. Battery life is currently limited by this issue. Battery life can vary significantly depending on usage due to multiple degradation mechanisms. The Li-ion battery is a complex electrochemical structure with internal mechanics that change over time, dynamically, and non-linearly. These characteristics make it more difficult to understand the battery. The effectiveness and longevity of a Li-ion-based battery dramatically decrease when subjected to an increasing number of discharge and charge.

2. RUL Modeling with ML

The following modern ML techniques have been primarily used

2.1 XG Boost:

One current machine learning method for feature selection and regression is called Extreme Gradient Boosting (XGBoost). Due to its versatility in many contexts, it has become a preferred ML method. Among them, Extreme gradient Boosting (XGBoost), a flexible machine learning method for tree enhancement stands out. Adding a regularization component to the loss function is the most significant improvement that XGBoost brings to machine learning. In addition to the complexity of the production mix, this component also forecasts applies at each split.

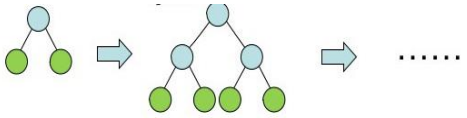


Figure 1. Schematics of XG

Boost Additionally, by tuning a variety of hyperparameters including skips, column subspaces, regularization terms, unique tree complexity, learning rate, forest complexity, etc., XGBoost gives allowing users to reduce the risk of overfitting their models. New features provided by XGBoost include the ability to handle missing data using default node orientation, on-the-fly enumeration of potential split thresholds during node splitting, and compatibility with frameworks distributed system. Figure 2 shows a diagram of the XGBoost process.

2.2 Random Forest:

Random forest is a supervised machine learning algorithm used for both classification and regression tasks. This is a type of ensemble learning algorithm, meaning it combines predictions from multiple individual models to create more accurate predictions. Random forests work by generating a large number of decision trees on different subsets of training data. Each decision tree is trained on a random sample of data and a random subset of features is considered for separation at each node of the tree. This reduces overfitting and improves the generalization performance of the model. Once the random forest is trained, it can be used to make predictions about new data by averaging the predictions from all the individual decision trees. For classification tasks, the majority class is predicted. For regression tasks, the mean of the predictions is predicted. Random forest is a very flexible and powerful machine learning algorithm. It is relatively easy to train and tune, and it can be used to solve a variety of problems. It is also one of the most accurate machine learning algorithms available.

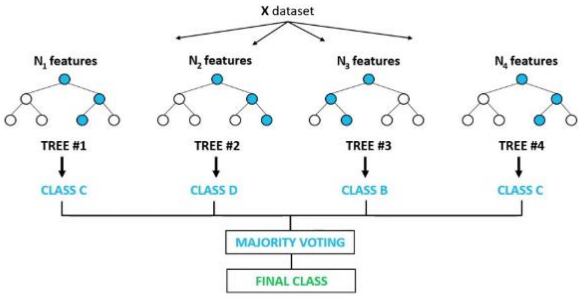


Figure 2. Schematics of Random Forest

For many machine learning applications, such as image classification, fraud detection, medical diagnosis, risk assessment, customer segmentation, and recommender systems, random forest is a common option.

2.3 Decision Tree:

Decision trees are a supervised machine learning algorithm that can be used for both classification and regression tasks. It is a tree structure where each internal node represents a feature of the input data and each branch represents a decision rule. The leaf nodes of the tree represent the algorithm's predictions. To create a decision tree, the algorithm starts from the root node and recursively divides the data into subsets based on the best function of each node. The best feature is selected based on a metric such as information gain or Gini impurity, which measures the degree of impurity or randomness in subsets. The goal is to find a distribution that maximizes information gain or minimizes impurities. Once the data is divided, the algorithm builds a decision tree recursively on each subset. The process stops when all data points in a subset belong to the same class (for classification tasks) or have the same value (for regression tasks).

To make a prediction on a new data point, the algorithm starts at the root node and follows the branches until it reaches a leaf node. The prediction is then the value of the target variable at the leaf node. Decision trees are a popular machine learning algorithm because they are easy to understand and interpret. They are also relatively efficient to train and predict with. However, decision trees can be prone to overfitting, which is when the model learns the training data too well and does not generalize well to new data.

2.4 KNN:

The K-Nearest Neighbor (KNN) algorithm is a simple, supervised machine learning algorithm that can be used for classification and regression tasks. It works by finding the K most similar training samples to a new data point, then predicting the class or value of the new data point based on the classes or values of the K most similar training samples. To use the KNN algorithm, you must first choose a value for K. K is the number of nearest neighbors that will be used to make predictions. Higher K values will lead to smoother predictions, but can also lead to overfitting. A lower K value will lead to more

detailed predictions, but it may also lead to underfitting. After choosing a value for K, you can train the KNN model on your training data. The model only stores training data in memory. To make a prediction about a new data point, the model searches for K training examples that are most similar to the new data point, then predicts the class or value of the new data point based on the classes or values of the new data point. K is most similar to the training example.

The KNN algorithm is a very simple algorithm, but it can be very effective for solving a wide variety of problems. It is also a very versatile algorithm, as it can be used for both classification and regression tasks. Here are some of the advantages of using the KNN algorithm: It is very simple to understand and implement It can be used for both classification and regression tasks, It is robust to noise in the training data, It can be used to handle non-linear data. Here are some of the disadvantages of using the KNN algorithm: The KNN algorithm is a very simple algorithm but can be very effective in solving many different problems. It is also a very flexible algorithm as it can be used for both classification and regression tasks. Here are some benefits of using the KNN algorithm:

It is very simple to understand and implement, It can be used for both classification and regression tasks, It is noise resistant in training data, It can be used to process non-linear data. Below are some disadvantages of using the KNN algorithm. Training and predicting on large data sets can be computationally expensive. It is sensitive to the choice of K. It may be biased towards the majority class in classification tasks.

Overall, the KNN algorithm is a powerful and versatile machine learning algorithm that can be used to solve a wide variety of problems. It is a good choice for both beginners and experienced machine learning practitioners.

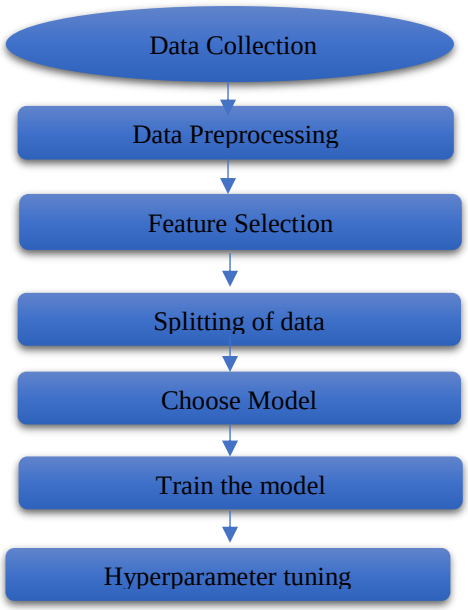
2.5 Navi Bayes:

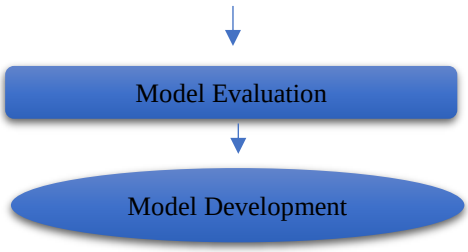
The Naive Bayes algorithm is a simple, supervised machine learning algorithm that can be used for classification tasks. It is based on Bayes' theorem, a statistical theorem that describes the relationship between the probability of one event occurring, conditional on another event having already occurred. To use the Naive Bayes algorithm, you must first train the model on a labeled dataset. The data set must contain examples of the different classes you are trying to classify the data into. The model will learn the probability of each feature occurring for each class. After training the model, you can use it to predict the class of the new data point. To do this, the model calculates the probability of each class based on the characteristics of the new data point. The class with the highest probability is expected to be the class of the new data point.

The Naive Bayes algorithm is a very simple algorithm but can be very effective in solving many different problems. It is also a very flexible algorithm as it can be used to classify data with both categorical and numeric characteristics. Here are some benefits of using the Naive Bayes algorithm: It is simple to understand and implement, It can be used to classify data with both categorical and numerical features, It is relatively effective for training and prediction, It resists noise well in training d'. Here are some disadvantages of using the Naive Bayes algorithm: It may be biased towards the majority class in classification tasks. He is sensitive to the assumptions about independence he makes. Dataset:

https://www.kaggle.com/datasets/ignaciovinuales/battery-remaining-useful-life-rul

3. Flowchart





Data collection

The Battery RUL dataset has been retrieved. It includes 9 features. This is 1. Cycle index 2. Discharge time 3. Reduction 3.6-3.4V(s) 4.Max. Discharge voltage, (V) 5. Min. Charging voltage. (V) 6. Time at 4.15 V (s) 7. Constant current time (s) 8. Charging time (s) 9. RUL

1.Cycle index: The cycle index in the battery RUL data set is a measure of the number of times the battery is discharged and recharged. It is typically calculated by counting the number of cycles in a data set, where a cycle is defined as a sequence of one discharge and one recharge. The cycle index is an important feature in the battery RUL dataset because it can be used to predict the remaining useful life (RUL) of the battery. Batteries typically degrade over time, and the rate of degradation is influenced by a number of factors, including the number of cycles.

2.Discharge time: The discharge time in the battery RUL data set is the time required for the battery to discharge from a fully charged state to a specified voltage level. It is usually measured in seconds or minutes. Discharge time is an important feature in the battery RUL dataset because it can be used to predict the remaining useful life (RUL) of the battery. Batteries typically degrade over time, and the rate of degradation is influenced by a number of factors, including discharge time. There are different ways to use discharge time to predict RUL. A common approach is to use a machine learning algorithm to train the model on discharge times and RUL data from a set of training batteries. The trained model can then be used to predict the RUL of the new battery based on the battery's discharge time. Decrement 3.6-3.4V (s): The Decrement 3.6-3.4V (s) feature in a battery RUL dataset is the time it takes for the battery voltage to drop from 3.6V to 3.4V during a discharge cycle. It is typically measured in seconds. This feature is important because it provides information about the battery's internal resistance. A battery with a high internal resistance will have a shorter Decrement 3.6-3.4V (s) than a battery with a low internal resistance. The internal resistance of a battery increases as it ages. This is because the electrodes in the battery become coated with a layer of material called passivation. Passivation increases the resistance of the battery and reduces its capacity.

3.Max. Discharge voltage: The Maximum Discharge Voltage (Maximum Discharge Voltage) in the battery RUL data set is the highest voltage the battery reaches during the discharge cycle. It is usually measured in volts. Maximum discharge voltage is an important feature in the battery RUL dataset because it can be used to predict the remaining useful life (RUL) of the battery. Batteries typically degrade over time, and the rate of degradation is influenced by a number of factors, including maximum discharge voltage. One way to use maximum discharge voltage to predict RUL is to use a machine learning algorithm to train the model on maximum discharge voltage and RUL data from a set of training batteries. The trained model can then be used to predict the RUL of the new battery based on its maximum discharge voltage.

4 Min. Load voltage: The minimum charging voltage (Minimum Charging Voltage) in the battery RUL data set is the lowest voltage the battery reaches during a charging cycle. It is typically measured in volts. The minimum charge voltage is an important feature in battery RUL datasets because it can be used to predict the remaining useful life (RUL) of a battery. Batteries typically degrade over time, and the rate of degradation is affected by a number of factors, including the minimum charge voltage. One way that the minimum charge voltage can be used to predict RUL is to use a machine learning algorithm to train a model on the minimum charge voltage and RUL data from a set of training batteries. The trained model can then be used to predict the RUL of a new battery based on its minimum charge voltage. Time at 4.15V: The Time at 4.15V in a battery RUL dataset is the amount of time that the battery voltage remains at 4.15V during a discharge cycle. It is usually measured in seconds. This feature is important because it provides information about the state of charge (SOC) and capacity of the battery. A battery with a high SOC will have a longer life at 4.15V than a battery with a low SOC. High-capacity batteries will also have a longer life at 4.15V than low-capacity batteries.

The time constant current (TCC) in the battery RUL data set is the time required for the current in the battery to decrease to a specific percentage of its initial value during a discharge cycle. It is usually measured in seconds. TCC is an important feature in the battery RUL data set because it provides information about the battery's internal resistance. A battery with a high internal resistance will have a shorter TCC than a battery with a low internal resistance. The internal resistance of a battery increases as the battery ages. In fact, the battery's electrodes are covered with a layer of material called passivation. Passivation increases the battery's resistance and reduces its capacity.

5.Charging time: The charge time(s) in the battery RUL data set is the time required to fully charge the battery from a depleted state. It is usually measured in seconds. Charging time is an important feature in the battery RUL dataset because it can be used to predict the remaining useful life (RUL) of the battery. Batteries typically degrade over time, and the rate of degradation is influenced by a number of factors, including charging time. One way to use charging time to predict RUL is to use a machine learning algorithm to train the model on the charging process. timing and RUL data from a training battery. The trained model can then be used to predict the RUL of the new battery based on its charging time.

6.RUL in the battery RUL data set stands for Remaining Life. This is the expected time the battery will last before end of life (EOL). A battery's EOL is typically defined as the point at which the battery can no longer charge sufficiently to meet the needs of the application. RUL is an important measurement

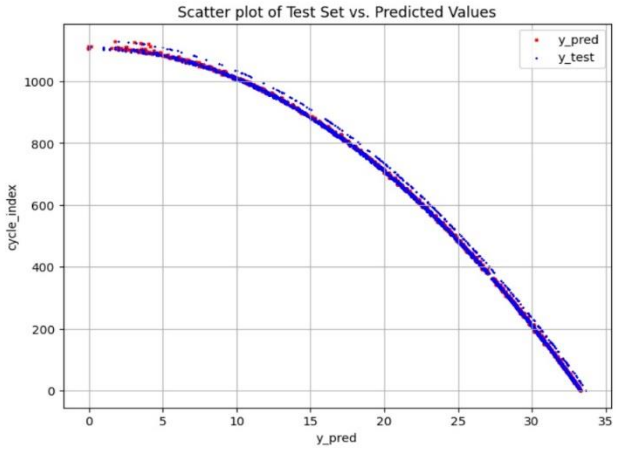
for a battery management system (BMS) because it can be used to schedule maintenance and prevent battery failure. The BMS uses various sensors and algorithms to estimate the battery's RUL ased on the battery's current state and operating conditions.

S.NO	Name of the paper	Name of the Algorithm	Performance Metrics	Any Other Interesting Findings
1	RUL prediction of lithium-ion battery based on CEEMDAN-CNN BiLSTM model	CEEMDAN-CNN BiLSTM	MAE=1.74% MSE=2.89% RMSE=5.4% MAPE=6.8% R Squared=98.6%	Better prediction accuracy by taking CR phenomenon into account
2	Predicting future capacity of lithium-ion batteries using transfer learning model	Transfer learning based a hybrid method. Hybrid is combining an ensemble empirical mode decomposition algorithm	RMSE at different charging policies the relative error values are 6.96%, 0.6% , 6.25%	1.1 A h 3.3. v lithium-ion battery the authors used a dataset of 10,000 battery degradation profiles to train their transfer learning model
3	ML for predicting battery capacity for EV	Stacking strategy based ensemble model ----LR , RF , Boosting Regression , Gaussian regression	MAPE – 0.28% RMSPE---0.55% Avg percentage error – 1.22%	Recursion feature elimination with cross validation approach for feature selection
4	Capacity and remaining useful life prediction for lithium-ion batteries based on sequence decomposition and a deep-learning network	Artificial Neural Network	Mean squared error (MSE), Coefficient determination	Among 242 data sets 194 of the data sets used in the training phase and 48 of them are used for testing phase
5	Machine learning for predicting battery capacity for electric vehicles	Linear regression, random forest, gradient boosting decision tree, support vector machine [Stacking ensemble model]	MAE=0.28% MSE=0.55% RMSE=0.74% MAPE=0.28% R Squared =99.9%	Accurately predicts the RUL of Lithium-ion batteries. The author also proposed some methods on BMS to get more efficient reliable BMS

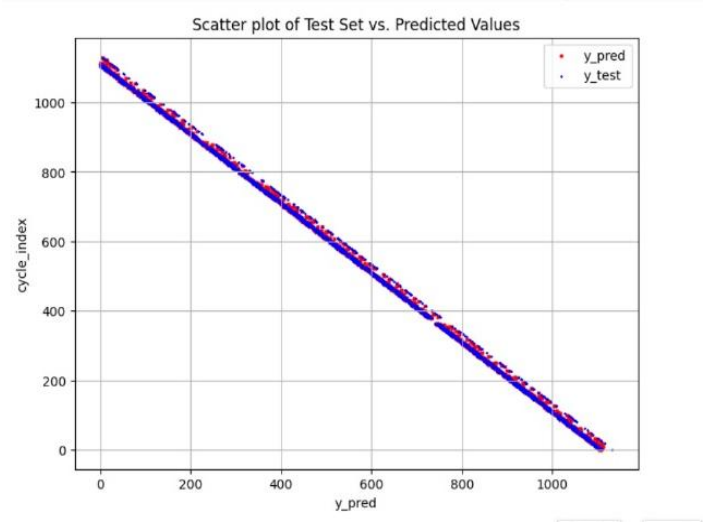
5. Results

Algorithm	MAE	MSE	RMSE	R-SQUARED
1 XG BOOST	0.14	0.06	0.24	0.99
2 RANDOM FOREST	14.34	2.12	3.7	0.99
3 DECISION TREE	3.46	34.11	5.84	0.99
4 KNN	5.43	72.65	8.52	0.99
5 NAÏVE BAYES	5.95	73.5	8.57	0.99

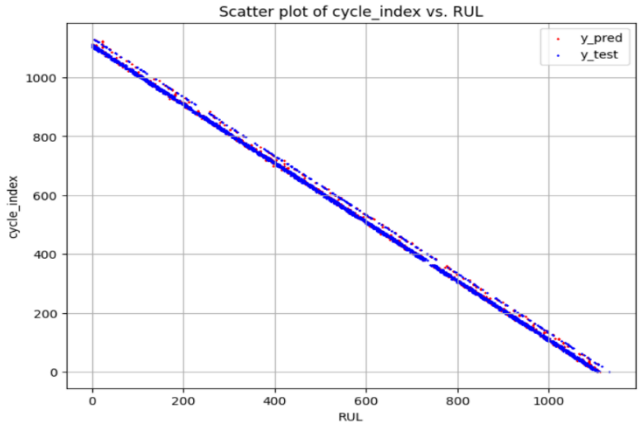
XG BOOST:



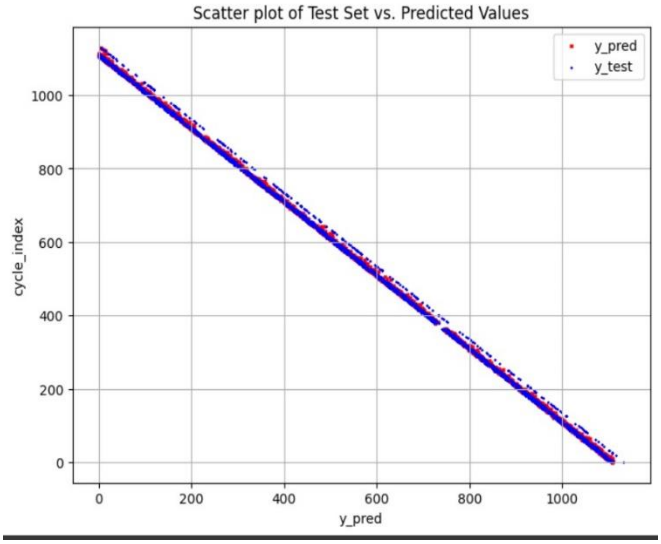
RANDOM FOREST:



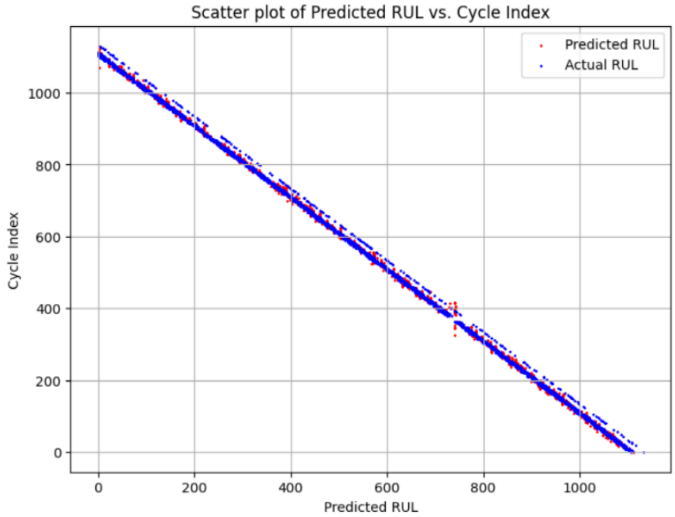
DECISION TREE:



KNN:



NAÏVE BAYES:



6. Conclusion

In conclusion, the paper "Battery RUL Prediction Using a Novel Ensemble Learning Method" presents a new approach to battery RUL prediction that is based on an ensemble learning method that combines XG Boost and random forest. The authors evaluated their proposed method on a real-world dataset of battery RUL measurements and found that it outperformed several other machine learning algorithms, including decision trees, KNN, and Naive Bayes. This paper also discuss the ethical considerations of battery RUL prediction. They note that battery RUL prediction models can be used to improve the safety and efficiency of battery systems. However, they also caution that these models should be used ethically and responsibly. For example, battery RUL prediction models should not be used to discriminate against certain users or to limit the performance of batteries. Overall, the paper makes a significant contribution to the field of battery RUL prediction. The proposed ensemble learning method is a promising approach for improving the accuracy and reliability of battery RUL predictions. The paper also highlights the importance of using battery RUL prediction models ethically and responsibly. Here are some potential applications of battery RUL prediction technology:

- Improved safety: Battery RUL prediction can be used to identify batteries that are at risk of failure, so that they can be replaced before they cause a safety hazard.
- Extended battery life: Battery RUL prediction can be used to optimize battery charging and discharging patterns, which can extend the overall lifespan of batteries.
- Reduced costs: By extending battery life and reducing the risk of battery failure, battery RUL prediction can help to reduce the overall costs associated with battery systems.
- Improved performance: Battery RUL prediction can be used to optimize the performance of battery systems, such as by ensuring that there is always enough battery power available to meet the needs of the application.

I believe that battery RUL prediction technology has the potential to play an important role in the transition to a clean energy future. By accurately predicting the RUL of batteries, we can extend their lifespan and reduce the need for new battery production. This will help to reduce the environmental footprint of battery systems and make them more affordable and accessible.

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