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Predictive analytics of battery use conditions and degradation: A data-driven approach

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Abstract

Lithium-ion batteries are the critical components of the latest energy storage devices, ranging from consumer electronics to electrically powered automobiles. Despite their significant applications in the storage of electrical energy devices, the functionality of these batteries largely relies on the nature of the charge/discharge cycles. Batteries subjected to complete charge/discharge cycles deteriorate faster than batteries that undergo partial cycles, which limits their possibility for reuse and recycling. Understanding and predicting battery consumption conditions can substantially help with lifecycle management and sustainable recycling initiatives. This study investigates a data-driven approach for predicting the use condition of lithium-ion batteries based on degradation criteria. Logistic regression, Naïve Bayes, and decision tree models are used to predict the previously used condition of a battery based on several variables such as days of degradation, energy throughput, C/10 capacity, and state of health (SoH). The dataset is collected from the existing literature and preprocessed to extract the required variables. After preprocessing and variable selection, the models are made and tested with cross-validation and ROC analysis. The analysis of the results suggests that the decision tree classifier performs better compared to other classification models in terms of accuracy, F1 score, and AUC values. The findings prove the applicability of the predictive analysis technique in assisting battery lifecycle management by categorizing the batteries that have been used in different scenarios for recharging.

Keywords: Lithium-ion battery, Predictive analytics, Machine learning, Battery recycling

1. Introduction

Lithium-ion batteries (Li-ion) have greatly impacted the energy storage system with their high energy density, extended lifespan, and high efficiency. These batteries find widespread use in consumer electronic devices, electrically powered automobiles, and renewable energy storage systems. However, the efficiency of Li-ion batteries deteriorates over a period of time due to many reasons, including aging cycles of the battery, high or low temperatures, the charge or discharge cycles of the battery, and the applications under different operating conditions. Accurate predictions of the usage conditions of these batteries, specifically whether they have been used through a full charge-discharge cycle or a short charge-discharge cycle, are critical for optimizing their life cycle management and assuring safety and efficiency in applications.

Full charge-discharge and short charge-discharge cycles both have a significant impact on a Li-ion battery's performance, durability, and overall health. Each cycle type causes different loads on the battery, altering its degradation and efficiency over time. A complete charge-discharge cycle involves charging the battery to its maximum capacity (100%) and then fully draining it (to 0% or close to it), which is often referred to as a deep cycle. Batteries that are subjected to complete charge-discharge cycles show more capacity deterioration than those cycled within a narrower voltage range because deep cycles cause lithium-ion batteries to deteriorate faster due to the chemical reactions that occur during the charge-discharge process and cause enormous stress on internal components.

As a result, the electrodes undergo structural changes that result in irreparable damage [1]. On the other hand, short charge-discharge cycles cause less stress on the battery than full cycles. When a battery is not fully charged or discharged, the electrodes undergo less strain, resulting in slower degradation. Operating in the partial SOC range reduces the rate of capacity loss. Previous studies have demonstrated that batteries cycled within narrower SOC ranges reveal slower deterioration rates compared to those exposed to complete cycles [2], [3]. A cell cycled with a 20%-80% state of charge (SOC) window has a much longer cycle life than those cycled with full 0%-100% SOC cycles, specifically, a cell with a lower DOD has a significantly higher number of cycles before hitting the end-of-life capacity criterion [4].

It is critical to determine whether a battery may be used in the future with minor maintenance or cannot be used at all when it is collected and sent to the recycling department after a time of usage. For this reason, a predictive data-driven model can be utilized to categorize and forecast the battery's state for future use. A battery that has previously been used under short cycle charge-discharge conditions can be used again because of its less degraded condition; if it has been used under full cycle charge-discharge conditions, it cannot be used again. It will be convenient to manage old batteries if a data-driven prediction model is employed to divide such used batteries into two categories: full cycle charge-discharge batteries and short cycle charge-discharge batteries. Figure 1 demonstrates a systematic workflow analysis to effectively maintain the battery recycling process using predictive modelling.

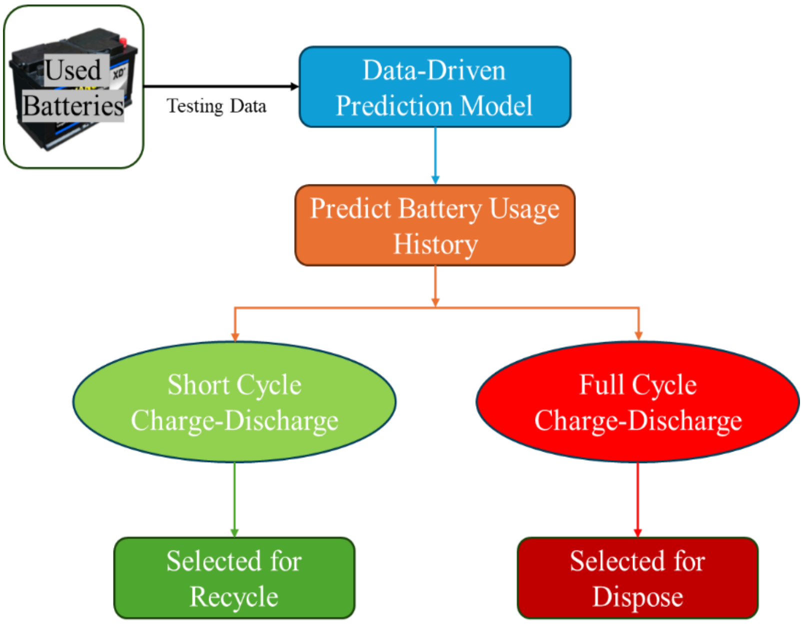

Figure 1. Predictive modeling workflow for battery recycling

Data-driven approaches have significantly advanced the field of predictive analytics, such as battery utilization and degradation. A deep learning-based prognostic model has been developed to show how data-driven methods may accurately forecast a battery's state of health (SoH) and remaining usable life (RUL) [5]. Tian et al. developed a technique for predicting voltage-capacity curves from single-cycle data, which allows for the early identification of battery degradation patterns [6].

Additionally, a study proposed a machine learning framework that employs data formation to predict the lifespan and classify battery quality, which demonstrates the efficiency of data-driven techniques in battery manufacturing with significant accuracy [7]. Moreover, the significance of early-cycle data in lifespan estimation was underscored by previous research, which emphasized the ability of machine learning models to predict battery cycle life before observable capacity degradation [8]. By combining data-driven methods with physical degradation models, physics-informed machine learning (PIML) has improved battery degradation diagnostics even further. A comparative analysis of many PIML techniques demonstrated their precision and suitability for predicting long-term deterioration from short-term aging data [9]. Sharma and Bora explored the advantages and disadvantages of several algorithms for predicting the remaining usable life (RUL) of lithium-ion batteries using contemporary machine learning techniques [10].

These developments highlight how crucial it is to combine machine learning and domain expertise to improve the accuracy and comprehensibility of battery health predictions. According to existing literature, ensemble techniques like random forest frequently perform better in terms of accuracy and stability than individual models, such as support vector regression (SVR), which makes them ideal for predicting the long-term health of batteries [11]. Figure 2 demonstrates the comparison of different models for battery health predictions.

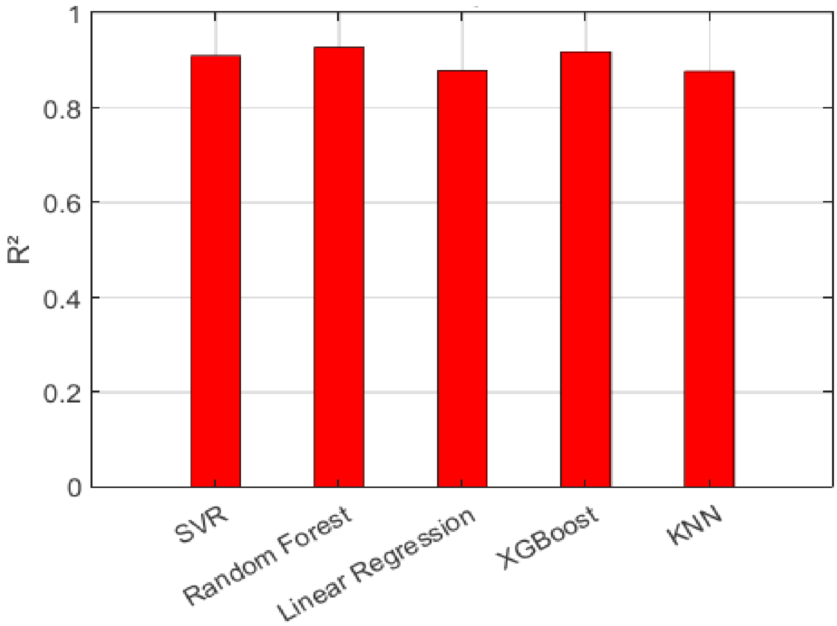

Figure 2. Comparison of different models [11]

Furthermore, predicting and tracking the health of lithium-ion batteries has demonstrated enhanced performance using hybrid approaches that combine random forest with other machine learning techniques [12]. The durability of a Naïve Bayes model across various operating situations was highlighted by its steady and competitive prediction performance when compared to Support Vector Machines for predicting the remaining usable life (RUL) of lithium-ion batteries under constant discharge environments [13]. To categorize battery charge and discharge states in a study on battery energy storage devices, researchers used logistic regression algorithms and decision trees. The models' high accuracy and performance metrics of about 95% demonstrate how well they work to optimize battery operation and health monitoring [14].

2. Research method

In this study, an experimental raw dataset is collected from an open-access data repository called Zenodo [15]. The collected dataset is related to a single lithium-ion battery degradation study where degradation mode analysis is performed [16]. While this dataset enables consistent comparison across degradation indicators, it represents a limited experimental population rather than the full diversity of batteries encountered in real-world recycling or second-life scenarios. From this data file, the extracted main data is used to collect all data in a separate Excel file, where different experiment results based on different cell types, different temperatures, and two different SoC ranges (0-30% SoC and 0-100% SoC) are tabulated. From the degradation modes file, SoH and capacity values are collected, and a total of 239 effective datapoints are stored in the final dataset file, which are evenly distributed between the two categories. Category A (CatA) represents batteries subjected to short charge–discharge cycling within a 0–30% state-of-charge (SoC) window, while Category B (CatB) represents batteries subjected to full charge–discharge cycling within a 0–100% SoC window. As both categories contain an equal number of samples, the dataset is balanced. Consequently, no class imbalance-handling techniques were applied in this study.

To prevent data leakage, model training and evaluation were performed using a strict separation between training and test datasets, and cross-validation was applied only within the training set. Although the proposed framework demonstrates strong classification performance, the results are derived from a dataset with limited variability in operating conditions, including temperature and cell chemistry. As a result, model sensitivity to these factors is not explicitly evaluated in the present study. The Alteryx platform is used to analyze data and build predictive models. Normal and Log-Normal distribution analysis are performed for every variable using the distribution analysis tool available in the Alteryx platform to see whether the data is normally distributed or skewed. Then, suitable variables are selected to perform predictive analysis.

Three different predictive models are selected, such as logistic regression, Naïve Bayes, and decision trees. The workflow of these models is created after the cleansing process of the data to improve the data quality by eliminating null values and removing rows related to zero values. After running all the models, the union tool is used to perform cross-validation of all the models. The model comparison tool is used to get the model performance of all the models, such as the average accuracy, F1 score, and ROC curves. Figure 3 demonstrates the flowchart of the whole process that is employed in this study.

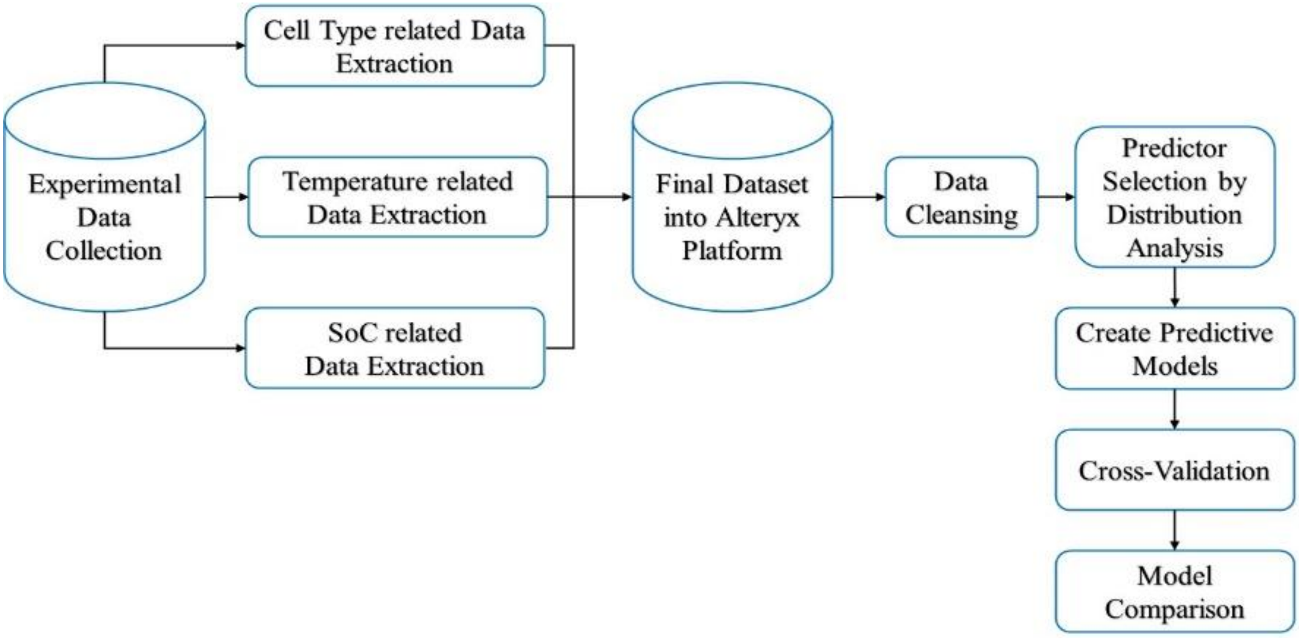

Figure 3. A systematic flowchart

Feature scaling was not applied in this study. Logistic regression was implemented in logit mode using the default configuration available in the Alteryx platform, and Naïve Bayes was implemented with Laplace smoothing set to zero, which is consistent with the platform's default settings. As all input variables were expressed in physically meaningful units and within comparable numerical ranges, additional normalization or standardization was not required. The decision tree classifier was implemented using the default hyperparameter settings provided by the Alteryx platform. Specifically, the minimum number of records required to allow a split was set to 20, the minimum number of records in a terminal node was set to 7, and the maximum tree depth was limited to 10 levels. Node splitting was based on information gain, and tree pruning was performed automatically during cross-validation to mitigate overfitting. No manual hyperparameter tuning was performed, as the primary goal was to evaluate baseline model performance and interpretability rather than optimize predictive accuracy.

Table 1 represents the variable number, variable name, and description of every variable. The target variable has two categorical values, "CatA" and "CatB", where "CatA" indicates short charge-discharge cycling (0% to 30% of SoC) and "CatB" indicates full charge-discharge cycling (0% to 100% of SoC). The four predictor variables ($X_1 - X_4$) were selected based on their established relevance in prior lithium-ion battery degradation studies and their practical availability in experimental and battery management system datasets. Specifically, the days of degradation (X_1) variable has been used as a temporal aging indicator to quantify cycle-driven degradation effects in lithium-ion batteries, as demonstrated by Preger et al. [4].

Energy throughput (X_2) was selected since cumulative charge and energy transfer have been shown to correlate strongly with electrochemical aging and capacity fade, which was employed in a degradation modeling study [2]. C/10 capacity (X_3) was included as a standardized low-rate capacity metric that reflects long-term capacity loss, which was used before for degradation assessment and cycle-life prediction in a prior work [8]. State of health (X_4) was selected as an aggregate degradation indicator, which was used in a data-driven health assessment model [5]. These variables are commonly reported in degradation studies and battery management systems, making them well-suited for recycling and second-life decision support, where advanced sensing data may not be available.

Table 1. Variables

Variable Number	Variable Name	Description
X_1	Days of degradation	The total number of days since the battery test began, representing the elapsed time of aging
X_2	Energy Throughput (W.h)	The total energy (Watt-hours) transferred through the battery over its usage. A higher value typically correlates with greater aging
X_3	C/10 Capacity (mA.h)	The battery's capacity is determined when discharged at a C/10 rate (a slow discharge rate). Used to assess long-term capacity fade
X_4	SoH	A measure of the battery's overall condition compared to its original state

3. Results and discussion

Figure 4 presents histograms with density plots comparing the distributions of variables to normal and lognormal fits. Days of degradation, energy throughput, and C/10 capacity exhibit right-skewed distributions where the lognormal fit captures the data better than the normal fit. On the other hand, SoH shows more symmetrical distributions.

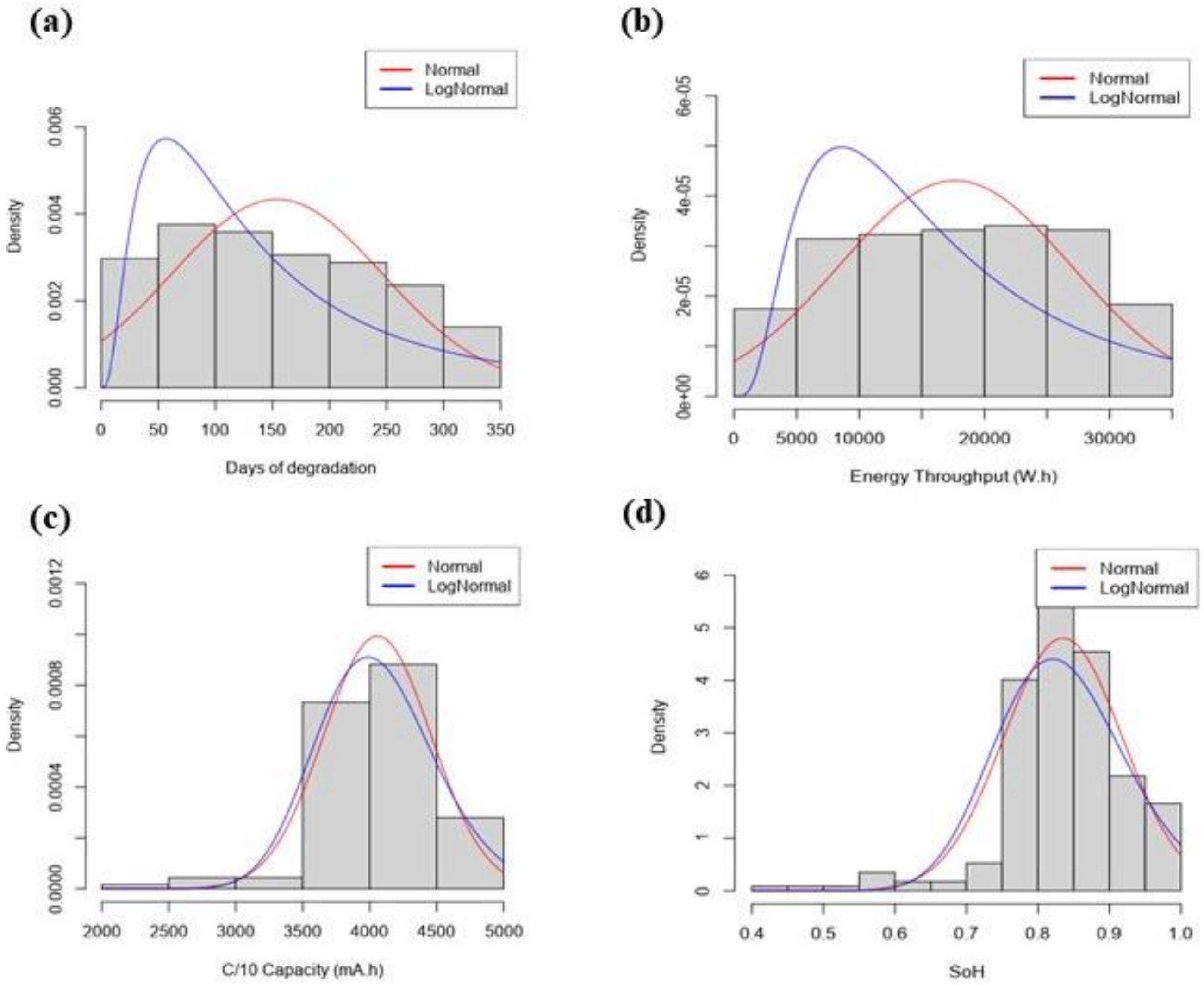

Figure 4. Distribution of variables (a) days of degradation, (b) energy throughput (W.h), (c) C/10 capacity (mA.h), (d) SoH

3.1. Logistic regression

A linear model for applications involving binary classification is logistic regression. Because of its mathematical simplicity and interpretability, it is used as a baseline model in the context of battery health prediction. However, the complicated and non-linear mechanisms involved in battery degradation may limit the ability of Logistic Regression to capture complex patterns [17].

3.2. Naïve Bayes

The Naïve Bayes classifier is a probabilistic model based on Bayes' theorem and assumes feature independence. Despite this assumption, it has been used to forecast battery RUL across various usage scenarios and environmental temperatures. Its simplicity and efficiency make it appropriate for cases involving low computer resources [18].

3.3. Decision tree

A decision tree is a nonlinear model that can recursively classify data depending on feature values, making it suitable for detecting complicated interactions. So, it can be used to predict battery usage condition especially for the classifier problem. In this study, a decision tree model is used to classify the used condition of a battery depending on various operating conditions. Figure 5 shows the decision tree algorithm performed in Alteryx software.

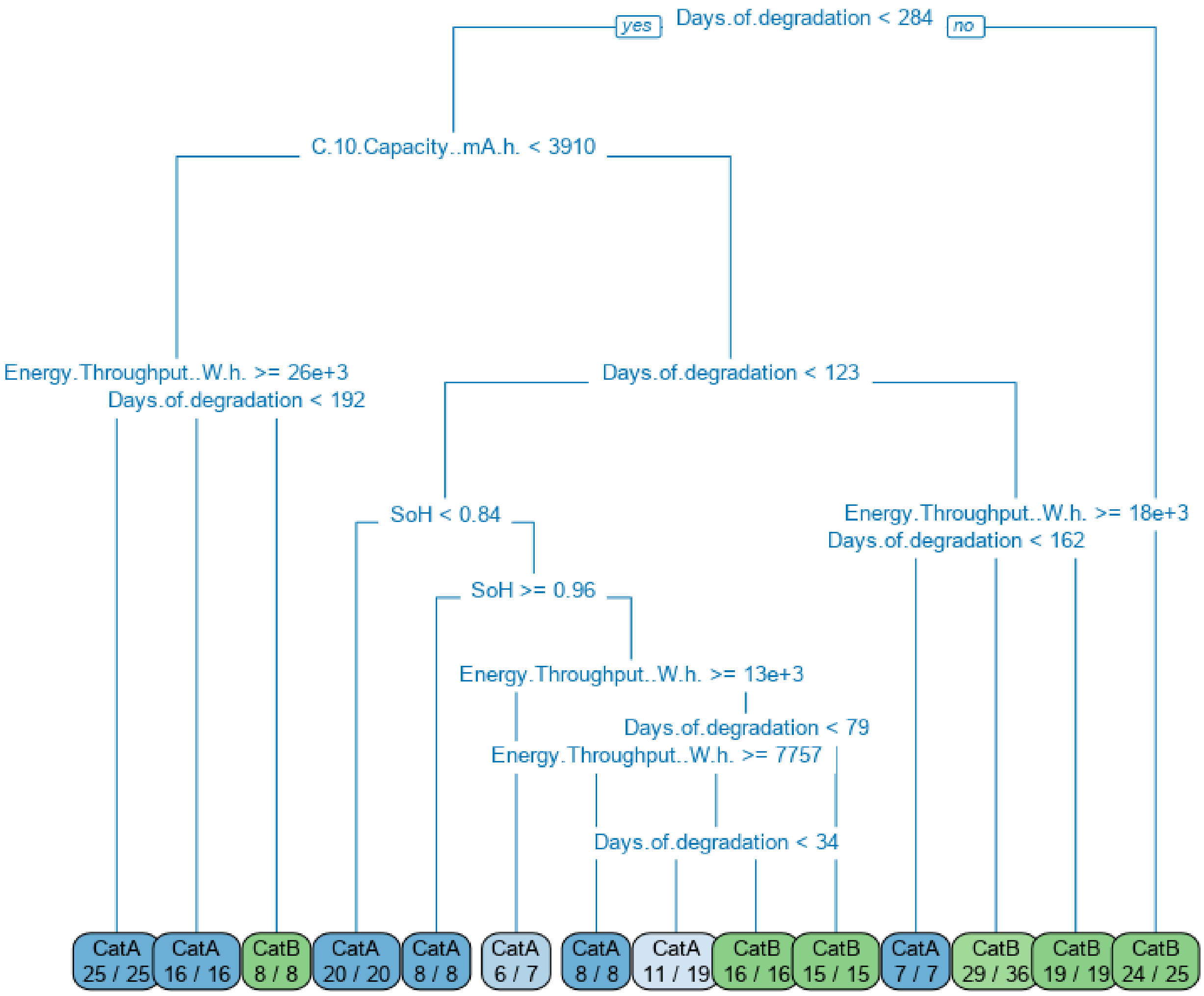

Figure 5. Decision tree algorithm

Three predictive models have been developed using k-fold cross-validation techniques to evaluate the performance of the models. The accuracy of the cross-validation and overall model performance are shown in Table 2 and Table 3, respectively, which show that the decision tree model surpasses logistic regression and Naïve Bayes. It has the highest overall accuracy (0.9258), F1 score (0.9224), and AUC (0.9792), with well-balanced accuracies for both categories (CatA: 0.9266, CatB: 0.9250), proving its durability and reliability. Logistic regression also performs well, with high accuracy (0.8821), AUC (0.9612), and a strong F1 score (0.8721), making it an alternative where interpretability is critical. The Naïve Bayes classifier performs poorly on this test, with low accuracy (0.6157), F1 score (0.4699), and AUC (0.7654), indicating limited applicability.

Table 2. Cross-validation accuracy

Model	Average Accuracy Class 1	Average Accuracy Class 2	Average Accuracy Overall
Logistic Regression	0.824317	0.907955	0.869147
Naïve Bayes	0.936335	0.965837	0.951981
Decision Tree	0.791459	0.718524	0.755652

The Naïve Bayes classifier performs well during cross-validation, but substantially lower on the independent test dataset. The Naïve Bayes algorithm involves conditional independence among input features, which accounts for this behavior. Key parameters in lithium-ion battery degradation datasets, such as state of health (SoH), capacity, and energy throughput, are physically and statistically connected due to common electrochemical aging mechanisms. Such relationships may lead to overly optimistic cross-validation results while also decreasing the model's capacity to generalize to new data. The Naïve Bayes classifier is computationally efficient and has good cross-validation metrics, but it is not as robust as models that can capture feature dependencies.

Table 3. Overall model accuracy

Model	Accuracy	F1	AUC	Accuracy of CatA	Accuracy of CatB
Logistic Regression	0.8821	0.8721	0.9612	0.8440	0.9167
Naïve Bayes	0.6157	0.4699	0.7654	0.3578	0.8500
Decision Tree	0.9258	0.9224	0.9792	0.9266	0.9250

The ROC curve (Receiver Operating Characteristic) is a graphical diagram used to assess the performance of a binary classification model. It illustrates the trade-off between the true positive rate (TPR) and the false positive rate (FPR) at various classification criteria. A model with a curve closer to the top-left corner shows higher performance. The true positive rate, also known as recall, is a measure of how successfully the model recognizes actual positives. This is plotted along the y-axis of the ROC curve.

$$\text{tp rate} = \frac{\text{Positives correctly classified}}{\text{Total positives}} \tag{1}$$

The false positive rate measures how frequently the model wrongly labels negatives as positive. This is represented along the x-axis of the ROC curve.

$$\text{fp rate} = \frac{\text{Negatives incorrectly classified}}{\text{Total negatives}} \tag{2}$$

Precision can be used in ROC analysis by assessing the reliability of positive predictions, but it is not directly used to generate the ROC curve. However, precision and recall are used to compute the F1 score reported in Table 3. Recall is the same as TPR and is critical in plotting the ROC curve.

$$\text{Precision} = \frac{\text{tp}}{\text{tp+fp}} \tag{3}$$

$$\text{Recall} = \frac{\text{tp}}{\text{tp+fn}} \tag{4}$$

$$\text{F1} = 2\,.\,\frac{\text{Precision . Recall}}{\text{Precision +Recall}} \tag{5}$$

The Receiver Operating Characteristic (ROC) curve is determined by the TPR or recall and the FPR based on the measurements taken from the confusion matrix values (True Positives, False Positives, True Negatives, and False Negatives). These metrics make it easier to examine the capacity of a model to deal with sensitivity (identification of positives) and specificity (avoidance of False Positives). The Area Under the ROC curve provides a threshold-independent measure of classification performance, where an AUC value of 1 indicates perfect classification and an AUC value of 0.5 corresponds to random guessing. In this study, the ROC curve and AUC are used to compare the separability and robustness of the classification models.

The area under the ROC curve in Figure 6 shows that the decision tree model performs better than the other two classifiers. It achieves the highest true positive rate despite almost all false positive rates and stays closest to the top-left corner, which denotes optimal classification. Logistic regression also shows good performance with a well-shaped ROC curve, although the ROC curve is slightly lower than that of the decision tree. On the other hand, the Naïve Bayes classifier shows the lowest classification performance since it has the lowest area under the curve.

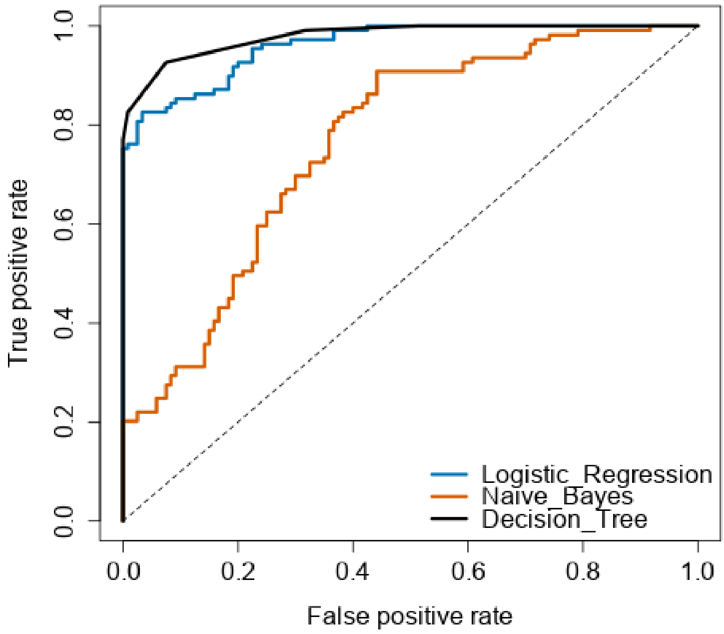

Figure 6. Receiver operating characteristics (ROC) curve

This work indicates that predictive analytics can be a strong tool for categorizing lithium-ion batteries based on their historical usage conditions, specifically differentiating between full and short charge-discharge cycles. In terms of accuracy (92.58%), F1 score (92.24%), and AUC (97.92%), the decision tree model outperformed logistic regression and Naïve Bayes, which indicates its ability to capture complex, nonlinear degradation patterns in battery systems. This discovery is consistent with previous observation [19], where it is shown that decision trees and related classifiers attain excellent accuracy (95%) when predicting battery charge and discharge states. Logistic regression performed reasonably well with an AUC of 96.12%, though less accurate than decision trees, which is consistent with its known merits in giving a basic, interpretable baseline model. However, as explained by a previous study [20], logistic regression frequently struggles to model the highly nonlinear dynamics causing battery depletion, limiting its predictive ability in complicated circumstances. Overall, the decision tree model has the most predictive power, followed by logistic regression, whereas Naïve Bayes is the least successful in this situation, with the lowest overall accuracy of 61.57% and an AUC of 76.54%.

4. Conclusions

Finally, this work successfully illustrates the use of predictive analytics to categorize lithium-ion batteries based on their previous charge-discharge cycles. It is specifically designed to classify historical battery usage conditions rather than state-of-health metrics, and its contribution is oriented toward recycling and second-life decision support rather than conventional performance prediction. The decision tree model beat the other two models (Logistic Regression and Naïve Bayes) in terms of accuracy, F1 score, and AUC, demonstrating its capacity to capture nonlinear deterioration patterns. Using this model, battery recycling processes can be accelerated. Logistic regression also performed well in this study.

However, Naïve Bayes showed limited applicability due to weak generalization. The use of a decision tree-based predictive model allows stakeholders within the battery industry to optimize battery reuse and recycling processes by informing decision-making on the potential reuse of the used Li-ion batteries, which is important for a more sustainable approach to the lifecycle management process of Li-ion batteries. Most current data-driven studies [21], [22] on lithium-ion batteries are concerned with estimating remaining usable life (RUL), capacity fading, or state of health under known operating conditions. In contrast, the current study focuses on the underexplored challenge of inferring prior battery usage conditions from deterioration indications. This work provides a complementary perspective to traditional lifetime prediction approaches by classifying batteries based on whether they were subjected to full or partial charge–discharge cycles. The proposed framework directly supports practical decisions involving battery reuse, second-life deployment, and recycling, where prior usage history often remains unknown.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The contribution to the paper is as follows: Khowshik Dey, Serkan Varol: study conception and design; Khowshik Dey: data collection; Khowshik Dey, Serkan Varol: data analysis and interpretation of results; Khowshik Dey, Serkan Varol: draft preparation. All authors approved the final version of the manuscript.

References

[1] G. Ning, B. Haran, and B. N. Popov, “Capacity fade study of lithium-ion batteries cycled at high discharge rates,” *Journal of Power Sources*, vol. 117, no. 1–2, pp. 160–169, May 2003, https://doi.org/10.1016/S0378-7753(03)00029-6.

[2] S. Saxena, C. Hendricks, and M. Pecht, “Cycle life testing and modeling of graphite/LiCoO2 cells under different state of charge ranges,” *Journal of Power Sources*, vol. 327, pp. 394–400, Sep. 2016, https://doi.org/10.1016/j.jpowsour.2016.07.057.

[3] N. R. Chowdhury, A. J. Smith, K. Frenander, A. Mikheenkova, R. W. Lindström, and T. Thiringer, “Influence of state of charge window on the degradation of Tesla lithium-ion battery cells,” *Journal of Energy Storage*, vol. 76, p. 110001, Jan. 2024, https://doi.org/10.1016/j.est.2023.110001.

[4] Y. Preger *et al.*, “Degradation of Commercial Lithium-Ion Cells as a Function of Chemistry and Cycling Conditions,” *J. Electrochem. Soc.*, vol. 167, no. 12, p. 120532, Jan. 2020, https://doi.org/10.1149/1945-7111/abae37.

[5] P. Khumprom and N. Yodo, “A Data-Driven Predictive Prognostic Model for Lithium-ion Batteries based on a Deep Learning Algorithm,” *Energies*, vol. 12, no. 4, p. 660, Feb. 2019, https://doi.org/10.3390/en12040660.

[6] J. Tian, R. Xiong, W. Shen, and J. Lu, “Data-driven battery degradation prediction: Forecasting voltage-capacity curves using one-cycle data,” *EcoMat*, vol. 4, no. 5, p. e12213, Sep. 2022, https://doi.org/10.1002/eom2.12213.

[7] J. Zou, Y. Gao, M. H. Frieges, M. F. Börner, A. Kampker, and W. Li, “Machine learning for battery quality classification and lifetime prediction using formation data,” *Energy and AI*, vol. 18, p. 100451, Dec. 2024, https://doi.org/10.1016/j.egyai.2024.100451.

[8] K. A. Severson *et al.*, “Data-driven prediction of battery cycle life before capacity degradation,” *Nat Energy*, vol. 4, no. 5, pp. 383–391, May 2019, https://doi.org/10.1038/s41560-019-0356-8.

[9] S. Navidi, A. Thelen, T. Li, and C. Hu, “Physics-informed machine learning for battery degradation diagnostics: A comparison of state-of-the-art methods,” *Energy Storage Materials*, vol. 68, p. 103343, Apr. 2024, https://doi.org/10.1016/j.ensm.2024.103343.

[10] P. Sharma and B. J. Bora, “A Review of Modern Machine Learning Techniques in the Prediction of Remaining Useful Life of Lithium-Ion Batteries,” *Batteries*, vol. 9, no. 1, p. 13, Dec. 2022, https://doi.org/10.3390/batteries9010013.

[11] S.-A. Amamra, “Random Forest-Based Machine Learning Model Design for 21,700/5 Ah Lithium Cell Health Prediction Using Experimental Data,” *Physchem*, vol. 5, no. 1, p. 12, Mar. 2025, https://doi.org/10.3390/physchem5010012.

[12] R. S. Kumar, A. R. Singh, P. L. Narayana, V. S. Chandrika, M. Bajaj, and I. Zaitsev, “Hybrid machine learning framework for predictive maintenance and anomaly detection in lithium-ion batteries using enhanced random forest,” *Sci Rep*, vol. 15, no. 1, p. 6243, Feb. 2025, https://doi.org/10.1038/s41598-025-90810-w.

[13] S. S. Y. Ng, Y. Xing, and K. L. Tsui, “A naive Bayes model for robust remaining useful life prediction of lithium-ion battery,” *Applied Energy*, vol. 118, pp. 114–123, Apr. 2014, https://doi.org/10.1016/j.apenergy.2013.12.020.

[14] R. Gilbert Zequera, V. Rjabtšikov, A. Rassõlkin, T. Vaimann, and A. Kallaste, “Modeling Battery Energy Storage Systems Based on Remaining Useful Lifetime through Regression Algorithms and Binary Classifiers,” *Applied Sciences*, vol. 13, no. 13, p. 7597, Jun. 2023, https://doi.org/10.3390/app13137597.

[15] N. Kirkaldy, M. A. Samieian, G. J. Offer, M. Marinescu, and Y. Patel, “Data from: ‘Lithium-ion battery degradation: measuring rapid loss of active silicon in silicon-graphite composite electrodes.’” Zenodo, Oct. 21, 2022. https://doi.org/10.5281/ZENODO.7235858.

[16] N. Kirkaldy, M. A. Samieian, G. J. Offer, M. Marinescu, and Y. Patel, “Lithium-Ion Battery Degradation: Measuring Rapid Loss of Active Silicon in Silicon–Graphite Composite Electrodes,” *ACS Appl. Energy Mater.*, vol. 5, no. 11, pp. 13367–13376, Nov. 2022, https://doi.org/10.1021/acsaem.2c02047.

[17] X. Wang, J. Meng, and T. Azib, “A Comparative Study of Data-Driven Early-Stage End-of-Life Classification Approaches for Lithium-Ion Batteries,” *Energies*, vol. 17, no. 17, p. 4485, Sep. 2024, https://doi.org/10.3390/en17174485.

[18] S. S. Y. Ng, Y. Xing, and K. L. Tsui, “A naive Bayes model for robust remaining useful life prediction of lithium-ion battery,” *Applied Energy*, vol. 118, pp. 114–123, Apr. 2014, https://doi.org/10.1016/j.apenergy.2013.12.020.

[19] R. Gilbert Zequera, V. Rjabtšikov, A. Rassõlkin, T. Vaimann, and A. Kallaste, “Modeling Battery Energy Storage Systems Based on Remaining Useful Lifetime through Regression Algorithms and Binary Classifiers,” *Applied Sciences*, vol. 13, no. 13, Art. no. 13, Jan. 2023, https://doi.org/10.3390/app13137597.

[20] X. Wang, J. Meng, and T. Azib, “A Comparative Study of Data-Driven Early-Stage End-of-Life Classification Approaches for Lithium-Ion Batteries,” *Energies*, vol. 17, no. 17, Art. no. 17, Jan. 2024, https://doi.org/10.3390/en17174485.

[21] S. Zhu *et al.*, “State of health and remaining useful life estimation of lithium-ion battery based on parallel deep learning methods,” *International Journal of Electrochemical Science*, vol. 20, no. 5, p. 100988, May 2025, https://doi.org/10.1016/j.ijoes.2025.100988.

[22] X. Lei, F. Xie, J. Wang, and C. Zhang, “A review of lithium-ion battery state of health and remaining useful life estimation methods based on bibliometric analysis,” *Journal of Traffic and Transportation Engineering (English Edition)*, vol. 11, no. 6, pp. 1420–1446, Dec. 2024, https://doi.org/10.1016/j.jtte.2024.09.004.