



Ensemble Learning-Based Fault Diagnosis of Electric Vehicle Lithium-Ion Batteries Using Operational Data

Merve PARLAK BAYDOGAN

Technical Sciences Vocational School, Computer Technologies Department, Firat University, Elazig, TURKEY

In this study, Lithium-ion batteries, while being the fundamental energy component of electric vehicles, can experience critical failures such as internal short circuits and over-discharge, triggering thermal runaway risks. This study proposes a high-accuracy, ensemble learning-based fault diagnosis system to improve operational safety in battery management systems (BMS). To this end, the model was trained using a numerical dataset of lithium-ion battery systems. Within the proposed methodology, the performance of eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LGBM), Random Forest (RF), Categorical Boosting (CatBoost), Extremely Randomized Trees (ExtraTrees), and Adaptive Boosting (AdaBoost) algorithms was analyzed in both binary and multi classification. The effectiveness of the models was evaluated using accuracy, sensitivity, recall, and F1 score. Experimental results show that ensemble learning-based methods exhibit consistent and balanced performance in both classification processes. In the binary classification process, the ExtraTrees model achieved the highest performance with 80.14% accuracy, while in the multi-classification process, the CatBoost model stood out with 92.64% accuracy and 0.9448 AUC. These findings demonstrate that ensemble learning-based approaches offer a viable and reliable framework for lithium-ion battery fault diagnosis problems.

Key words: Machine learning, Lithium-Ion Batteries, Electric vehicle, Ensemble methods

Submission Date: 24 September 2025

Acceptance Date: 05 December 2025

*Corresponding author: mpbaydogan@firat.edu.tr

1. Introduction

Lithium-ion batteries have become the primary power source for electric vehicles due to their high energy density, long cycle life, and low self-discharge rates. However, these batteries can experience critical failures such as capacity loss, internal short circuits (ISC), and thermal runaway (TR) due to manufacturing defects, overcharging/discharging, mechanical impact, or environmental factors. A small failure in one cell of the battery system can quickly spread to neighboring cells, leading to catastrophic consequences such as fire or explosion. Therefore, early detection of battery failures is crucial for both safety and maintenance costs [1-3].

In the literature, battery fault diagnosis methods are generally categorized into four main approaches: knowledge-based, model-based, signal processing-based, and data-driven. Knowledge-based methods rely on expert systems and fuzzy logic principles; model-based methods

simulate the physical behavior of the battery using equivalent circuit models (ECM) or mathematical equations, and analyze the deviations (residuals) between the measured data and the model outputs. In signal processing-based studies, techniques such as Empirical Mode Decomposition (EMD) or Sample Entropy are commonly used to decompose and denoise battery voltage signals [4,5].

The complexity of traditional methods, requiring complex physical models and adapting to changing operating conditions, has led researchers to data-driven methods and machine learning (ML) algorithms [6]. Data-driven approaches have the ability to learn fault patterns directly from operational data (voltage, current, temperature) without the need to model complex electrochemical processes. The literature reports that algorithms such as Support Vector Machines (SVM), RF, Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks demonstrate high accuracy in battery state

prediction and fault classification. Gradient boosting-based algorithms, in particular, stand out for their high accuracy even with low data quality. In recent years, tree-based gradient boosting algorithms such as XGBoost, LGBM, and CatBoost have gained prominence in complex classification problems due to their low computational costs and resistance to overfitting [7-9].

In the literature, studies on battery failure diagnosis mostly focus on single models or specific ensemble methods. Furthermore, studies that evaluate failure states together under binary and multi-class structures and comparatively examine the performance of different ensemble-based approaches are limited. This study presents a comprehensive analysis using ensemble-based algorithms (XGBoost, LGBM, RF, CatBoost, ExtraTrees, AdaBoost) with a lithium-ion battery dataset to detect different failure levels in electric vehicle batteries. The performance of Ensemble Learning techniques is compared in both binary (2-classes) and multi-class (3-classes) classification, thus aiming to determine the most optimized diagnostic framework for early failure detection.

2. Literature Review

Lithium-ion batteries are the primary energy component of electric vehicles. Therefore, identifying critical safety risks such as short circuits and thermal runaway in these batteries is of paramount importance. The complexity and high computational costs of traditional physical models have led researchers to artificial intelligence methods. This section presents studies in the literature aimed at detecting failures in lithium-ion batteries.

The study by Li et al., aimed to extract and diagnose fault characteristics from noisy voltage signals in electric vehicle batteries. The dataset used in the study consisted of real-world electric vehicle operating data and voltage and current measurements obtained from Urban Dynamometer Driving Schedule (UDDS) tests conducted in a laboratory environment. As a method, Empirical Mode Decomposition (EMD) technique was applied to decompose the voltage signals, and Sample Entropy analysis was performed on these decomposed signals to determine fault levels. The findings of the study revealed that the proposed method could detect both ordered degradation processes and sudden internal short-circuit faults with high accuracy, with a false alarm rate of 16.7% and a zero miss rate [5].

Li et al., aimed to develop a system that could detect and locate faults in battery cells earlier than traditional methods. In this study, a real-time operational dataset collected over one year from 10 electric buses operating in Suzhou, China, was analyzed. For the first time, kurtosis was used as a

method for fault detection; after the alarm was triggered, Multidimensional Scaling (MDS) and Density-Based Spatial Clustering (DBSCAN) algorithms were combined to identify faulty cells. The findings showed that this method could detect faulty cells one day before the original vehicle system and yielded more robust results compared to other unsupervised learning methods [10].

In the study conducted by Yu et al., the aim was to develop an unsupervised multimodal diagnostic framework that can predict battery thermal runaway events one week in advance using real-world electric vehicle data. The dataset used in the research consisted of operational data with a sampling rate of 0.1 Hz, collected from vehicles suspected of combustion or thermal runaway, obtained from a Chinese automotive company's big data platform. As a method, voltage signals were converted into time-frequency spectrograms using Short-Time Fourier Transform (STFT); Convolutional Neural Networks (CNN) were used to extract features from these images, and KPCA was used for dimensionality reduction. The findings of the study demonstrated that the proposed deep learning model could detect thermal runaway an average of 11 days in advance, achieving an AUROC value of 88.6%, and reducing accident costs by 33%-50% compared to traditional methods [11].

Huang et al., aimed to improve the effectiveness of deep learning in diagnosing faults such as micro short circuits and overcharging in battery packs. The study used a total of 1283 operational records containing charging and short circuit faults as the dataset. The method employed integrated Gram Angle Field (GAF) technique, which converts one-dimensional data into two-dimensional images, a Noise Reducing Autoencoder (DAE) for noise reduction, and a Transformer architecture with an attention mechanism to learn complex relationships in the data. The study's findings confirmed that the model demonstrated superior performance with 93.18% accuracy and a 0.95 F1 score, exhibiting high stability, particularly in detecting early-stage overcharging faults in retired battery packs [12].

Kosuru and Venkitaraman aimed to develop an intelligent diagnostic system to detect and classify faulty sensor data and transmission faults in battery management systems (BMS). The study utilized raw data collected from lithium-ion battery sensors. As a method, the Enhanced Sea Hunters Algorithm (EMPA) was applied for feature selection, and a bat-optimized deep residual network structure called the Incipient Bat-Optimized Deep Residual Network (IB-DRN) was established for final diagnosis. The findings showed that the proposed deep learning model achieved a 98% accuracy rate, yielding much more accurate and reliable results than traditional artificial neural networks ANN and SVM [13].

3. Materials and Methods

In this section, detailed information about the dataset used in the study and the proposed Ensemble learning-based model is presented.

3.1. Materials

This study utilizes a dataset created for fault detection and state of health (SoH) analysis of lithium-ion battery cells used in electric vehicles. The dataset was obtained from the EV Lithium-Ion Battery Fault Diagnosis Dataset published on the Mendeley Data platform [14]. Within the scope of this shared dataset, two different datasets based on battery modeling were developed in MATLAB for training and validating ANN based models. Both datasets used state of charge (SOC), temperature, and cell voltage parameters as input variables.

First Data Set (Binary Classification): The primary goal in this stage is to determine the overall health status of the battery. Batteries are categorized as "healthy" (label 0), representing normal operating conditions, and "unhealthy" (label 1), representing any anomalies [14]. The data set consists of a total of 728 samples, with 364 samples for each battery state, ensuring a balanced distribution of classes. Detailed information about the data set is provided in Table 3.1.

Table 3.1. Transposed Class-wise Statistical Summary of the EV Battery Fault Dataset (Mean \pm Std)

Feature / Class	Normal (0)	Fault (1)
Number of Samples (n)	364	364
SOC (mean \pm std)	53.49 \pm 27.46	33.51 \pm 39.79
Temperature (mean \pm std)	340.55 \pm 29.67	374.13 \pm 45.34
Voltage (mean \pm std)	3.48 \pm 0.26	3.21 \pm 0.37

Second Data Set (Multiple Classification): A more detailed classification is presented to improve the diagnostic capabilities of BMS. This includes data on the "healthy" (0) condition, as well as data on over-discharge fault (1) which shortens battery life and short-circuit fault (2) which triggers the risk of thermal runaway [14]. Detailed information about the data set is given in Table 3.2.

Table 3.2. Transposed Statistical Summary of the Multi-Class EV Battery Fault Dataset (Mean \pm Std)

Feature / Class	Healthy (0)	Over-Discharge (1)	Short-Circuit (2)
Number of samples (n)	424	364	364
SOC (mean \pm std)	52.23 \pm 28.08	33.51 \pm 39.79	-1922.67 \pm 1442.92
Temperature (K, mean \pm std)	337.05 \pm 26.72	374.13 \pm 45.34	23889.78 \pm 16455.96
Voltage (V, mean \pm std)	3.49 \pm 0.26	3.21 \pm 0.37	0.00 \pm 0.00

3.2. Methods

This study utilizes ensemble learning-based supervised machine learning methods that overcome the limitations of single models and possess higher generalization capabilities for diagnosing faults in lithium-ion battery systems. Ensemble learning approaches offer higher accuracy, better generalizability, and more stable prediction performance compared to single classifiers by combining the outputs of multiple base learners [16]. Ensemble methods provide an effective solution, particularly for problems exhibiting nonlinear and complex behaviors, such as battery systems. In this study, both binary (2-class) and multi-class (3-class) battery fault diagnosis approaches are considered, and a comparative evaluation is made using the same ensemble algorithms in both cases. The methods used consist of XGBoost, LGBM, RF, CatBoost, Extra Trees and AdaBoost algorithms. The flowchart of the proposed system is given in Figure 1.

The proposed system shown in Fig. 1 begins by receiving numerical data from battery cells as input, and this data is subjected to a preprocessing process that includes feature extraction, normalization, and training-test data separation. Following the preprocessing steps, the obtained features are analyzed using a heterogeneous ensemble learning structure consisting of XGBoost, LGBM, Random Forest, CatBoost, ExtraTrees, and AdaBoost algorithms. The proposed approach is structured to support both two-class and three-class classification processes. In the two-class dataset, battery status is considered as normal and faulty, while in the three-class dataset, healthy, over-discharge fault, and short-circuit fault classes are considered. In the final stage, the performance of the developed system is quantitatively evaluated using standard evaluation criteria such as accuracy, precision, sensitivity, and F-score.

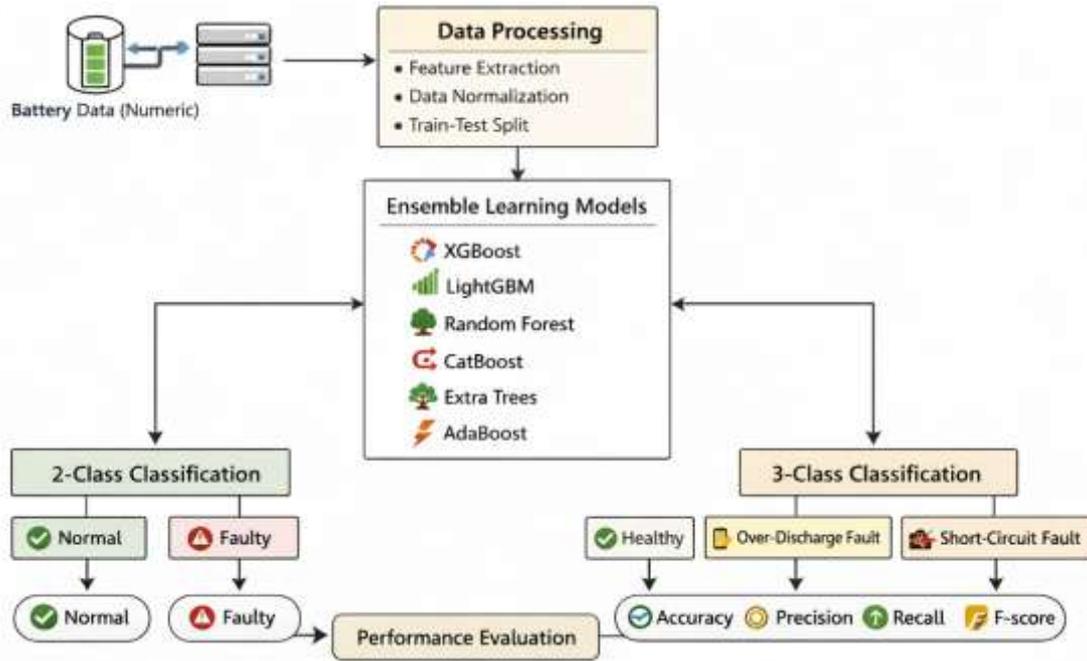


Figure 3.1. Workflow of the Proposed Ensemble-Based EV Battery Diagnostic System

Accuracy represents the overall classification performance of the model; Precision reflects the impact of false positive predictions, while Recall indicates the capture rate of true positive samples, especially in critical applications such as fault detection. The F-score reveals the balance between Precision and Recall, while the AUC metric summarizes the classifier's discriminatory power under different threshold values. Using these metrics together, the performance of the proposed ensemble learning-based models has been comprehensively analyzed. The equations corresponding to the performance metrics are presented below (Equations 1–4) [15].

$$Accuracy = \left(\frac{TP + TN}{(TP + FP + FN + TN)} \right) \quad (1)$$

$$Precision = \left(\frac{TP}{(TP + FP)} \right) \quad (2)$$

$$Recall = \left(\frac{TP}{(TP + FN)} \right) \quad (3)$$

$$F - score = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall} \right) \quad (4)$$

4. Experimental Results and Discussion

In this study, an ensemble learning-based classification approach developed for fault diagnosis of lithium-ion batteries was comprehensively evaluated under both binary (2-class) and multi-class (3-class). In the binary classification, battery states were considered as Normal and Faulty, while in the multi-class, three different battery states

were considered: Healthy, Over-Discharge Fault, and Short-Circuit Fault.

The performance of the models was measured using Accuracy, Precision, Recall, F-score, and AUC metrics to comprehensively evaluate classification accuracy, inter-class discrimination, and fault detection performance. In addition, the sensitivity levels of different ensemble algorithms, especially in the detection of critical fault types, were examined, and the class-based performance differences of the models were analyzed. The findings indicate that evaluating performance metrics together allows for a more comprehensive interpretation compared to analyses based solely on overall accuracy values. The experimental results obtained comparatively reveal the behavior of the ensemble methods used in different classification, and detailed performance values are presented in Table 4.1.

According to Table 3, the binary classification considers battery states under two categories, namely Normal and Faulty. Examining the results, it is seen that ensemble-based methods generally exhibit similar performance, but some models stand out significantly. In particular, the ExtraTrees algorithm achieved the highest performance in the binary classification with Accuracy, Precision, Recall, and F-score values above 80%. This indicates that the ExtraTrees method, thanks to its highly random tree structure, can more effectively capture complex patterns within the data.

Table 4.1. Performance Comparison of Ensemble Learning Models for Binary and Multi-Class Battery Fault Diagnosis

Types	Algorithm	Performance Evaluation Criteria				
		Accuracy	Precision	Recall	F-score	AUC
2-classes	XGBoost	0.7603	0.7607	0.7603	0.7602	0.7603
	LGBM	0.7603	0.7603	0.7603	0.7603	0.7603
	RF	0.7671	0.7673	0.7671	0.7671	0.7671
	CatBoost	0.7808	0.7810	0.7808	0.7808	0.7808
	ExtraTrees	0.8014	0.8019	0.8014	0.8013	0.8014
	AdaBoost	0.6918	0.7173	0.6918	0.6825	0.6918
3-Classes	XGBoost	0.8961	0.8985	0.8975	0.8979	0.9221
	LGBM	0.9048	0.9071	0.9060	0.9064	0.9286
	RF	0.9004	0.9026	0.9021	0.9023	0.9253
	CatBoost	0.9264	0.9296	0.9308	0.9282	0.9448
	ExtraTrees	0.8658	0.8706	0.8662	0.8673	0.8994
	AdaBoost	0.8355	0.8704	0.8291	0.8275	0.8766

In the three-class classification, battery states were evaluated under three classes: Healthy, Over-Discharge Fault, and Short-Circuit Fault. Despite the more complex problem structure, it is noteworthy that the models generally achieved higher performance values compared to binary classification. In particular, the CatBoost algorithm stood out as the most successful model in the multi-class with over 92% Accuracy and over 94% AUC. CatBoost's symmetrical tree structure and robust regularization mechanisms allowed it to learn the distinction between classes more effectively. Figure 4.1 presents the complexity matrices of the most successful models for both classification processes.

Fig. 4.1.(a) presents the complexity matrix of the Ensemble ExtraTrees model, which achieved the highest performance in binary classification. As seen in the matrix, the model correctly classified 60 of the samples belonging to the Normal (Class 0) class, while it incorrectly predicted 13 samples as Defective (Class 1). Similarly, 57 of the samples in the Defective (Class 1) class were correctly identified, while 16 samples were incorrectly classified as Normal. These results show that the model exhibits high and balanced classification performance for both classes. In particular, the correct identification of a large proportion of the defective battery samples reveals that the model offers reliable performance in terms of fault diagnosis.

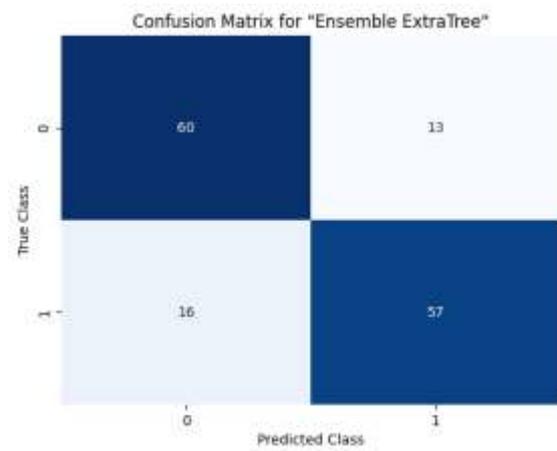
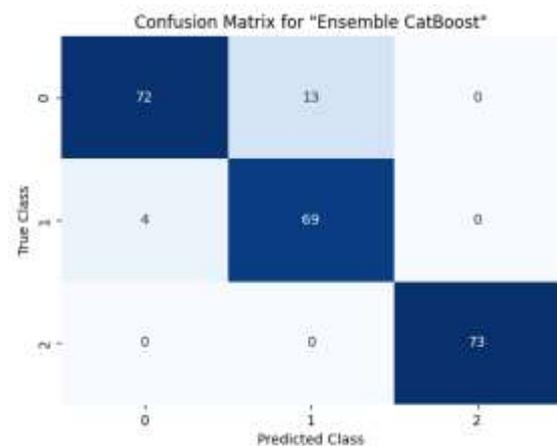
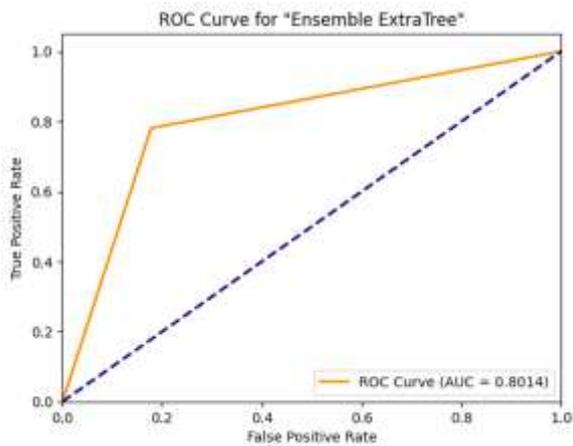
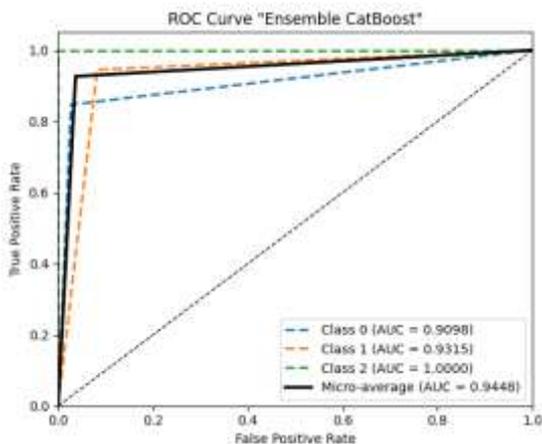
**a) 2-Classes-Ensemble ExtraTree****b) 3-Classes - Ensemble CatBoost****Figure 4.1.** Confusion matrices of the best-performing ensemble models for (a) binary and (b) multi-class battery fault classification

Figure 4.1.(b) presents the complexity matrix of the Ensemble CatBoost model, which exhibited the highest performance in the 3-class classification process. As seen in the matrix, 72 of the samples belonging to the Healthy (Class 0) class were correctly classified, while 13 samples were incorrectly classified as Over-Discharge Fault (Class 1). In contrast, 69 of the samples in the Over-Discharge Fault (Class 1) class were correctly identified, and only 4 samples were incorrectly classified as Healthy. On the other hand, the complete and accurate classification of all samples (73 samples) belonging to the Short Circuit Fault (Class 2) class demonstrates that the CatBoost model can distinguish this critical fault type from other classes with perfect separation. This reveals that the model has effectively learned the distinct and distinctive effects of short circuit faults on battery behavior. The Roc curve for these models is given in Figure 4.2.



a) 2-Classes-Ensemble ExtraTree

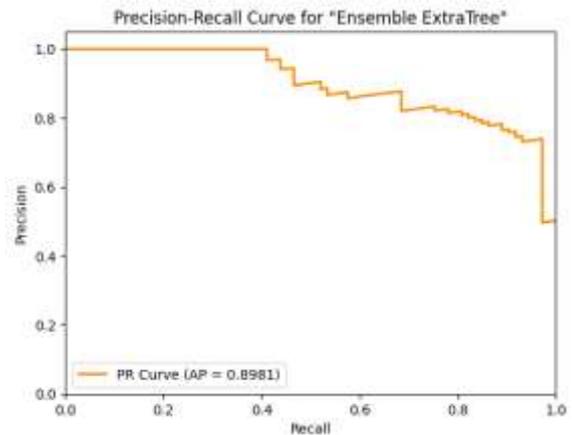


b) 3-Classes - Ensemble CatBoost

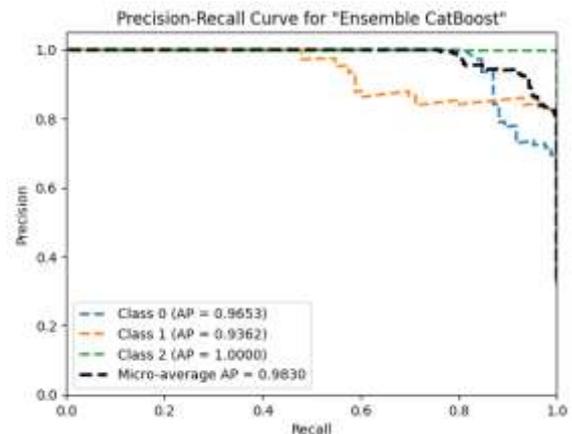
Figure 4.2. ROC curve (a) the two-class ensemble Extra Trees model and (b) three-class ensemble CatBoost model.

Fig. 4.2.(a) presents the ROC curve of the Ensemble ExtraTrees model used for the binary classification problem. The fact that the curve lies above the reference line

representing random classification indicates that the model successfully distinguishes between classes. The AUC value obtained in this classification is 0.8014, revealing that the model's ability to distinguish between Normal and Faulty battery states is satisfactory. Fig. 4.2.(b) shows the ROC curves of the Ensemble CatBoost model for the multi-class classification problem. In the class-based evaluation, AUC values of 0.9098, 0.9315, and 1.0000 are obtained for the Healthy, Over-Discharge, and Short-Circuit Fault classes, respectively. Furthermore, the macro-average AUC value of 0.9448 shows that the model exhibits a high discrimination performance across all classes. While ROC curves reveal the general discriminatory capabilities of the models, they may not provide a sufficient assessment on their own, especially for problems where the positive class is critical, such as fault diagnosis. Therefore, Precision-Recall (PR) curves were also examined to more clearly analyze the impact of false positive and false negative predictions. PR curves, by visualizing the balance between Precision and Recall metrics, which reflect the accuracy of correctly identifying faulty battery samples, allow for a more detailed evaluation of the models' performance under practical use conditions [17]. PR curves are shown in Fig. 4.3.



a) 2-Classes-Ensemble ExtraTree



b) 3-Classes - Ensemble CatBoost

Figure 4.3. PR curves for (a) 2-class Ensemble ExtraTrees and (b) 3-class Ensemble CatBoost

Fig. 4.3.(a) presents the PR curve of the Ensemble ExtraTrees model used for the binary classification problem, showing that the Average Precision (AP) value of 0.8981 indicates that the model maintains satisfactory precision, especially at high recall levels. Fig. 4.3(b) shows the class-based PR curves of the Ensemble CatBoost model for the multi-class classification problem. For the Healthy (Class 0), Over-Discharge Fault (Class 1), and Short-Circuit Fault (Class 2) classes, AP values of 0.9653, 0.9362, and 1.0000 were obtained, respectively, while the micro-average AP value of 0.9830 shows that the model offers a balanced and high fault detection performance across all classes.

The experimental results obtained in this study demonstrate that ensemble learning-based classification models exhibit consistent and comparable performance in lithium-ion battery fault diagnosis problems. Accuracy, Precision, Recall, F-score, ROC, and Precision-Recall analyses calculated with binary and multi-class datasets reveal in detail the behavior of the models used in terms of different evaluation criteria. In particular, it was observed that some ensemble methods offered higher discrimination in certain failure types with the multi-class dataset.

Results

This study proposes an ensemble learning-based classification approach for fault diagnosis of lithium-ion batteries used in electric vehicles, and the method is comprehensively evaluated with both binary (2-class) and multi-class (3-class) datasets. Experimental analyses performed using numerical battery data revealed the comparative behavior of different ensemble algorithms in battery fault detection. The results show that ensemble learning-based methods offer high accuracy and strong discrimination in battery fault diagnosis problems. While the ExtraTrees model exhibited balanced and stable performance in binary classification, the CatBoost model was found to provide superior performance, especially in distinguishing critical fault types, in multi-class classification. ROC and Precision-Recall analyses revealed that these models are effective not only in terms of overall accuracy but also in accurately identifying faulty samples. This study is limited to simulation-based numerical data, and more realistic evaluations can be performed in future studies using real-time vehicle data and online learning approaches.

References

- [1] Liao, L., Li, X., Yang, D., Wu, T., & Jiang, J. (2024). Fault diagnosis method for lithium-ion batteries based on the combination of voltage prediction and Z-score. *International Journal of Green Energy*, 21(14), 3270-3287. doi: 10.1080/15435075.2024.2376707.
- [2] Wang, S., Fernandez, C., Yu, C., Fan, Y., Cao, W., & Stroe, D. I. (2020). A novel charged state prediction method of the lithium ion battery packs based on the composite equivalent modeling and improved splice Kalman filtering algorithm. *Journal of power sources*, 471, 228450. doi: 10.1016/j.jpowsour.2020.228450.
- [3] Han, W., & Zhang, L. (2017). Mathematical analysis and coordinated current allocation control in battery power module systems. *Journal of Power Sources*, 372, 166-179. doi:10.1016/j.jpowsour.2017.10.046
- [4] Xiong, R., Sun, W., Yu, Q., & Sun, F. (2020). Research progress, challenges and prospects of fault diagnosis on battery system of electric vehicles. *Applied Energy*, 279, 115855. Doi: 10.1016/j.apenergy.2020.115855.
- [5] Li, X., Dai, K., Wang, Z., & Han, W. (2020). Lithium-ion batteries fault diagnostic for electric vehicles using sample entropy analysis method. *Journal of Energy Storage*, 27, 101121. doi: 10.1016/j.est.2019.101121
- [6] Wang, P., Chen, J., Lan, F., Li, Y., & Feng, Y. (2024). Multiscale feature fusion approach to early fault diagnosis in EV power battery using operational data. *Journal of Energy Storage*, 98, 112812 doi: <https://doi.org/10.1016/j.est.2024.112812>.
- [7] Sundaram, K. M., Hussain, A., Sanjeevikumar, P., Holm-Nielsen, J. B., Kaliappan, V. K., & Santhoshi, B. K. (2021). Deep learning for fault diagnostics in bearings, insulators, PV panels, power lines, and electric vehicle applications—the state-of-the-art approaches. *IEEE Access*, 9, 41246-41260. DOI: 10.1109/ACCESS.2021.3064360
- [8] Zhang, Z., Cao, R., Jin, Y., Lin, J., Zheng, Y., Zhang, L., Gao, X., & Yang, S. (2023). Battery leakage fault diagnosis based on multi-modality multi-classifier fusion decision algorithm. *Journal of Energy Storage*, 72, 108741. <https://doi.org/10.1016/j.est.2023.108741>.
- [9] Tang, A., Wu, Z., Xu, T., Wu, X., Hu, Y., & Yu, Q. (2024). Week-level early warning strategy for thermal runaway risk based on real-scenario operating data of electric vehicles. *ETransportation*, 19, 100308. Doi: <https://doi.org/10.1016/j.etrans.2023.100308>.
- [10] Li, F., Min, Y., & Zhang, Y. (2022). A Novel Method for Lithium-Ion Battery Fault Diagnosis of Electric Vehicle Based on Real-Time Voltage. *Wireless Communications and Mobile Computing*, 2022(1), 7277446. Doi: <https://doi.org/10.1155/2022/7277446>
- [11] Yu, Q., Yang, Y., Tang, A., Wu, Z., Xu, Y., Shen, W., & Zhou, F. (2025). Unsupervised learning for lithium-ion batteries fault diagnosis and thermal runaway early warning in real-world electric vehicles. *Journal of Energy Storage*, 109, 115194. doi: <https://doi.org/10.1016/j.est.2024.115194>.

- [12] Huang, J. C., Shu, M. H., Lin, H. T., & Day, J. D. (2024). Transformer-based lithium battery fault diagnosis research for electric vehicles. *Journal of Intelligent & Fuzzy Systems*, 46(4), 9329-9341. DOI: <https://doi.org/10.3233/JIFS-237796>
- [13] Kosuru, V. S. R., & Kavasseri Venkitaraman, A. (2023). A smart battery management system for electric vehicles using deep learning-based sensor fault detection. *World Electric Vehicle Journal*, 14(4), 101. doi: <https://doi.org/10.3390/wevj14040101>.
- [14] Veeramsetty, V., Janagani, S. V., & Pragnia, P. (2024). *EV lithium-ion battery fault diagnosis dataset* (Version 1) [Data set]. Mendeley Data. <https://doi.org/10.17632/t42ynjk936.1>.
- [15] Junker, M., Hoch, R., & Dengel, A. (1999, September). On the evaluation of document analysis components by recall, precision, and accuracy. In *Proceedings of the Fifth International Conference on Document Analysis and Recognition. ICDAR'99 (Cat. No. PR00318)* (pp. 713-716). IEEE. DOI: [10.1109/ICDAR.1999.791887](https://doi.org/10.1109/ICDAR.1999.791887)
- [16] XU, J. W., & YANG, Y. (2018). A survey of ensemble learning approaches. *Journal of Yunnan University: Natural Sciences Edition*, 40(6), 1082-1092.
- [17] Miao, J., & Zhu, W. (2022). Precision–recall curve (PRC) classification trees. *Evolutionary intelligence*, 15(3), 1545-1569. doi:10.1007/s12065-021-00565-2