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MACHINE LEARNING-BASED DRIVETRAIN FAULT CLASSIFICATION IN NEW ENERGY VEHICLES

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ABSTRACT

New Energy Vehicles (NEVs) represent an important direction in the development of sustainable transportation. The drivetrain of NEVs operates under changing electrical, mechanical, and environmental conditions, which can affect system stability and component integrity. Faults in the motor, inverter, and battery can interrupt power delivery, reduce operational continuity, and create risks for vehicle performance. This study presents an evaluation of machine learning methods for classifying drivetrain operating states using a structured dataset that contains measurements of voltage, current, motor speed, temperature, vibration, ambient temperature, and humidity. Three ensemble tree-based machine learning models, Random Forest, XGBoost, and CatBoost, are developed to classify four labeled states: normal condition, motor fault, inverter fault, and battery fault. Each model is trained and tested using common performance indicators, including accuracy, precision, recall, F1 score, and computation time. The experimental results demonstrate that ensemble learning models achieve high and stable classification performance across all drivetrain operating conditions, with XGBoost exhibiting the best balance between accuracy and computational efficiency. To enhance practical applicability, a real-time fault diagnosis demonstration is implemented, confirming the model's suitability for onboard systems. The findings indicate that machine learning can support automatic identification of drivetrain faults and contribute to diagnostic procedures, maintenance planning, and system reliability improvement in NEVs applications.

Keywords: New Energy Vehicles Drivetrain, Fault Classification, XGBoost, CatBoost, Random Forest.

1. INTRODUCTION

The automotive industry is undergoing a significant transformation driven by global efforts to achieve sustainable transportation and reduce carbon emissions, positioning New Energy Vehicles (NEVs) as a cornerstone of the future. NEVs comprise electric vehicles (EVs), plug-in hybrid electric vehicles (PHEVs), and hydrogen fuel cell vehicles (FCEVs) [1]. However, the safety and reliability of NEVs remain critical concerns, largely due to potential faults in core drivetrain components: the electric motor, power electronic converters (inverter), and battery system, as shown in Figure 1. Failures in these components lead to performance degradation and can result in severe consequences. For example, approximately 30% of EV accidents are reportedly caused by battery faults, and switching device failures are estimated to account for around 38% of problems in AC motor drives [2]. Therefore, implementing effective and timely Fault Detection and Diagnosis (FDD) is essential to maximize component lifespan and ensure operational safety.

Historically, FDD approaches are categorized as model-based, signal-based, data-driven (knowledge-based), and hybrid methods [2]. Model-based techniques rely on precise mathematical representations, while signal-based methods analyze signal patterns. These methods, however, are limited by their sensitivity to the high nonlinearity, parameter uncertainties, and dynamic load conditions inherent in NEV systems, often requiring considerable expert knowledge. Data-driven approaches that utilize Artificial Intelligence (AI) offer a strong alternative to traditional fault diagnosis techniques because they can automatically learn complex fault characteristics directly from historical sensor data without requiring explicit physical models. Within the AI domain, Machine Learning (ML) algorithms have become particularly important for fault diagnosis due to their ability to process large volumes of data and identify subtle patterns that are difficult to detect using conventional analytical methods [3]. This capability makes ML especially well-suited for addressing the inherent complexity of NEV drivetrain systems, which operate under diverse and continuously varying electrical and mechanical conditions.

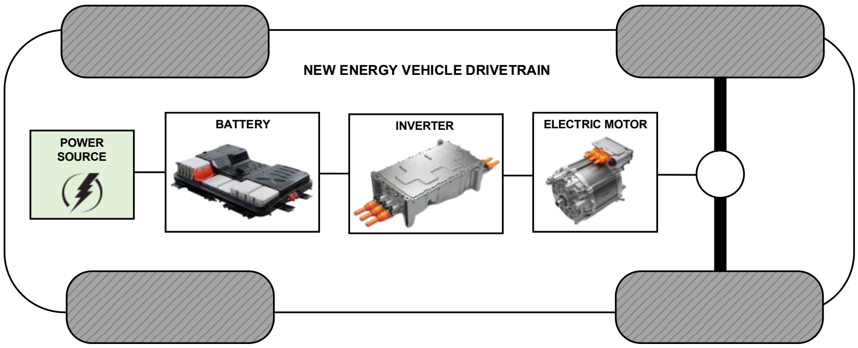


Fig 1. New Energy Vehicles (NEVs) drivetrain.

Recent research has consistently shown that machine learning methods are effective for fault diagnosis in electric drive systems, where data-driven classifiers are able to distinguish fault categories directly from multi-sensor measurements and outperform traditional rule-based and threshold-based diagnostic techniques. Early studies applying machine learning to electric motor drives demonstrated that classifiers such as decision trees and Random Forest can accurately identify motor and sensor faults, enabling early anomaly detection in traction systems and improving diagnostic reliability [4]. Subsequent investigations expanded these approaches to electric vehicle applications by benchmarking data-driven fault detection and diagnosis strategies, including Random Forest, gradient boosted decision trees (GBDT), and neural networks, against classical analytical methods. The results consistently indicated that machine learning-based FDD frameworks achieve superior fault detection performance, particularly under nonlinear operating conditions and parameter uncertainties typical of electric vehicle drivetrains [5]. Machine learning models trained on vehicle-level sensor data have also been successfully applied to battery management systems, demonstrating accurate fault classification and prediction capability for battery-related and propulsion-related faults in electric vehicles [6]. These studies highlight the suitability of supervised learning methods for handling complex fault patterns that are difficult to model explicitly using physics-based approaches. In addition, ensemble learning and hybrid classifier systems have been reported to achieve higher accuracy and robustness under noisy measurements and varying operating conditions, emphasizing the importance of model diversity and feature interaction handling in multi-class fault classification problems [7]. Comprehensive reviews of data-driven fault detection and diagnosis for electric drives further confirm a clear transition from model-based and signal-based techniques toward supervised machine learning frameworks that automatically extract discriminative fault features from large-scale sensor data without requiring detailed system models [8]. Within this evolving research landscape, gradient boosting decision tree methods such as XGBoost and CatBoost have gained increasing attention due to their high classification accuracy, robustness to feature interactions, and computational efficiency. These characteristics indicate strong potential for applying gradient boosting decision tree models to multi-class drivetrain fault classification in NEVs, which motivates their selection and systematic evaluation in the present study.

In this study, three decision tree-based machine learning models, namely Random Forest, XGBoost, and CatBoost, are evaluated for classifying four drivetrain operating states, including normal operation, motor faults, inverter faults, and battery faults. The evaluation is conducted using a balanced New Energy Vehicles diagnosis dataset designed for drivetrain fault classification. The dataset contains structured multi-sensor measurements such as voltage, current, motor speed, temperature, vibration, ambient temperature, and humidity. To improve data suitability for machine learning, feature transformations are applied to reduce skewness and enhance numerical stability. The objective of this work is to identify a robust and effective classification approach for automated multi-class fault diagnosis in NEV drivetrains. The experimental results demonstrate differences in model performance, with XGBoost achieving the best balance between classification accuracy and computational efficiency. This study not only compares the performance of three state-of-the-art ensemble tree-based models but also addresses a gap in prior work by demonstrating real-time fault classification, highlighting the practical deployment potential of the proposed approach in onboard diagnostic systems. The capability of these models to provide consistent classification using multi-sensor data directly supports the creation of efficient diagnostic procedures and effective maintenance planning for NEV applications.

The remainder of this paper is organized as follows: Section 2 describes the characteristics of the NEV drivetrain fault dataset. Section 3 presents the proposed methodology, including data preprocessing, classification models, and evaluation metrics. Section 4 discusses the results and discussion. Finally, Section 5 concludes the paper and outlines future research directions.

2. NEW ENERGY VEHICLES (NEVS) DATASET DESCRIPTION

This study employs a fault diagnosis dataset for New Energy Vehicles that is developed to support drivetrain fault classification [9]. The dataset provides labeled operating data representing both normal and faulty conditions of critical drivetrain components, including the electric motor, power electronic inverter, and battery system, which directly affect vehicle safety and operational reliability. The dataset consists of structured multi-sensor measurements collected from onboard vehicle systems. Each data sample is described by numerical features such as voltage, current, motor speed, temperature, vibration, ambient temperature, and humidity. These variables collectively capture the electrical behavior, mechanical condition, thermal characteristics, and environmental influences of the drivetrain under different operating conditions.

The dataset includes four labeled operating states. Label 0 represents normal operation and contains 5000 samples, accounting for 45.45% of the total dataset, as illustrated in Figure 2. Labels 1, 2, and 3 correspond to motor-related faults, inverter-related faults, and battery-related faults, respectively. Each fault category contains 2000 samples and represents 18.18% of the dataset. This distribution indicates that the dataset is not perfectly balanced, with normal operation forming the majority class. From a data structure perspective, the dataset is organized in a tabular format, where each row corresponds to an independent observation and each column represents a measured sensor variable or a fault label. This representation is well-suited for machine learning based fault diagnosis, particularly for algorithms that operate on structured numerical inputs. The tabular nature of the data allows classification models to directly exploit relationships among sensor features without requiring complex signal transformations or domain-specific feature extraction procedures.

Overall, the dataset is well structured and suitable for machine learning based fault classification. Although the presence of class imbalance may bias learning toward the normal operating state, it reflects realistic operating scenarios in New Energy Vehicles. With appropriate preprocessing and class weighting strategies, the dataset enables effective training and evaluation of machine learning models for automated drivetrain fault diagnosis and supports the development of intelligent condition monitoring and maintenance systems.

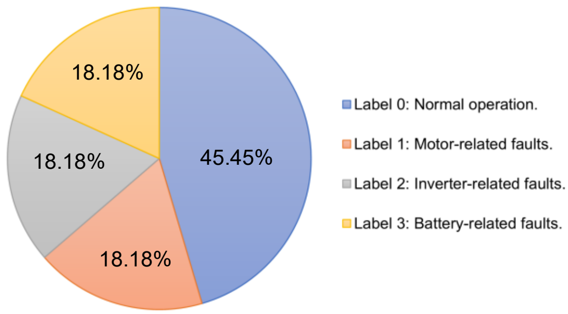


Fig 2. Label distribution of NEVs dataset.

3. METHODOLOGY

3.1. Data preprocessing

Prior to model training, a systematic data preprocessing procedure is applied to enhance data quality, numerical stability, and learning efficiency of the classification models. The original dataset is provided in a structured tabular format, where each row corresponds to a single operating instance of the NEV drivetrain and each column represents a measured sensor variable or the associated fault label. Since machine learning models are sensitive to data quality and feature scaling, preprocessing plays a critical role in ensuring reliable and reproducible classification performance.

First, missing values in the feature set are handled using constant imputation. Any missing sensor readings are replaced with zero values to maintain dataset completeness and prevent training interruptions caused by undefined numerical entries. This approach ensures that all samples retain a consistent feature dimensionality and can be processed uniformly by the classifiers. Given the relatively small proportion of missing values, constant imputation provides a simple and effective solution without introducing significant bias into the dataset.

Next, feature normalization is performed using Z-score standardization. Each numerical feature is transformed by subtracting its mean value and dividing by its standard deviation. This procedure rescales all input variables to have zero mean and unit variance, thereby eliminating discrepancies arising from different physical units and measurement ranges among voltage, current, speed, temperature, vibration, and environmental variables. Z-score normalization is particularly beneficial for distance-sensitive learning algorithms and gradient-based optimization processes, as it improves numerical stability and accelerates convergence during training.

After preprocessing, the dataset is partitioned into training and testing subsets using a hold-out strategy. Specifically, 80% of the samples are randomly assigned to the training set, while the remaining 20% are reserved for independent testing. The split is performed at the sample level to ensure that all fault categories are proportionally represented in both subsets.

This separation enables an unbiased evaluation of model generalization performance on unseen data.

The resulting preprocessed dataset, consisting of normalized numerical features, encoded class labels, and appropriately weighted samples, provides a consistent and reliable input for the classification models. This preprocessing pipeline establishes a standardized foundation for the subsequent development and evaluation of Random Forest, XGBoost, and CatBoost classifiers, which are described in the following subsection.

3.2. Classification models

3.2.1. Random Forest

Random Forest (RF) is an ensemble-based supervised learning algorithm that combines multiple decision trees to achieve robust and stable classification performance [10]. In this study, RF is selected as a baseline ensemble model for drivetrain fault classification in New Energy Vehicles due to its strong capability to handle structured, multi-sensor tabular data and its robustness under noisy and uncertain operating conditions. The RF algorithm employs Bootstrap Aggregation (Bagging), where each decision tree is trained on a randomly sampled subset of the training data with replacement [10]. In the implemented model, the number of trees is set to 2000 to ensure sufficient ensemble diversity and stable convergence of classification performance. At each split node, only a random subset of features is considered, which reduces correlation among trees and improves generalization capability. To address potential class imbalance in the fault dataset, a balanced class-weighting strategy is applied during training, allowing minority fault classes to contribute equally to the learning process.

For multi-class fault diagnosis, each decision tree produces an individual class prediction, and the final predicted fault label is determined by majority voting across all trees in the ensemble. The model is trained using Bootstrap Aggregation with out-of-bag (OOB) sampling enabled, which provides an internal estimate of generalization performance without requiring additional validation data.

3.2.2. XGBoost

Extreme Gradient Boosting (XGBoost) is a scalable and efficient implementation of gradient boosting decision trees, widely adopted for classification tasks involving structured and high-dimensional data [11]. In this study, XGBoost is employed to address the multi-class drivetrain fault classification problem in New Energy Vehicles, where complex nonlinear relationships exist among electrical, mechanical, thermal, and environmental sensor measurements. Unlike bagging-based ensemble methods, XGBoost follows a boosting strategy in which decision trees are built sequentially, and each new tree is trained to correct the prediction errors of the previous ensemble. This error-driven learning mechanism allows XGBoost to progressively improve fault discrimination capability, particularly for classes that are difficult to separate, such as motor, inverter, and battery faults with overlapping sensor characteristics. The model optimizes a regularized objective function that combines a differentiable loss term with penalty terms on model complexity, thereby balancing classification accuracy and generalization performance.

In the implemented model, XGBoost is configured with a maximum of 5000 boosting trees and a relatively small learning rate to allow gradual error correction. Tree depth is set to a moderate-to-high value to capture nonlinear feature interactions among drivetrain sensors, while subsampling and column sampling strategies are applied to reduce overfitting and improve robustness. Regularization terms, including L1 and L2 penalties, are incorporated to constrain model complexity. Early stopping is employed based on validation performance to automatically determine the optimal number of boosting iterations and prevent over-training.

3.2.3. CatBoost

CatBoost is a gradient boosting decision tree algorithm designed to improve learning stability and generalization performance, particularly for structured and heterogeneous datasets [12]. In this study, CatBoost is employed as an advanced boosting-based classifier for multi-class drivetrain fault diagnosis in New Energy Vehicles and is evaluated alongside Random Forest and XGBoost. Although CatBoost was originally developed to handle categorical features effectively, its core advantages extend beyond categorical data processing. The algorithm incorporates ordered boosting and symmetric decision tree structures, which significantly reduce prediction shift and overfitting during training. These characteristics make CatBoost well-suited for the NEV drivetrain dataset used in this work, which consists of multi-sensor numerical measurements collected under varying electrical, mechanical, thermal, and environmental operating conditions.

The CatBoost model is configured with a large number of boosting iterations and a moderate learning rate to balance convergence speed and classification accuracy. Tree depth and regularization parameters are selected to capture nonlinear sensor interactions while controlling overfitting. A class-weighting strategy is directly incorporated into the training process to address class imbalance in the fault dataset. Similar to XGBoost, early stopping based on validation performance is used to automatically determine the optimal number of boosting iterations.

3.3. Performance evaluation metrics

The performance of the proposed classification models is evaluated using standard and widely accepted metrics, including accuracy, precision, recall, F1-score, and computation time. These metrics are selected to provide a comprehensive assessment of the models' effectiveness in identifying normal and faulty operating conditions in New Energy Vehicle drivetrains.

Accuracy measures the overall correctness of a classification model and represents the proportion of correctly classified samples among all test samples. It is defined as in equation (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Where TP denotes true positives, TN denotes true negatives, FP denotes false positives, and FN denotes false negatives. In this study, accuracy provides an initial indication of model performance across all drivetrain operating states. However, since accuracy may be influenced by class distribution, it is not sufficient on its own to fully evaluate fault classification performance.

Precision evaluates the reliability of the model when predicting a specific fault type and is defined as in equation (2).

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

This metric reflects the proportion of correctly identified fault samples among all samples predicted as that fault. High precision indicates a low false alarm rate, which is particularly important in NEV fault diagnosis to avoid unnecessary inspections, maintenance actions, or system interruptions caused by incorrect fault alarms.

Recall measures the ability of the model to detect actual faults and is defined as in equation (3).

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

This metric indicates how many true fault cases are successfully identified by the classifier. In the context of drivetrain fault diagnosis, recall is a critical metric because undetected faults may lead to performance degradation, reduced system reliability, or potential safety risks during vehicle operation.

The $F1 - Score$ combines precision and recall into a single metric and is defined as in equation (4).

$$F1 - Score = 2\frac{Precision.Recall}{Precision + Recall} \tag{4}$$

This metric provides a balanced evaluation of classification performance by considering both false positives and false negatives. The $F1 - Score$ is especially useful in multi-class fault diagnosis tasks, where trade-offs between fault detection capability and false alarm reduction must be carefully considered. To ensure that all drivetrain operating states are evaluated fairly, macro-averaged precision, recall, and $F1 - Score$ are employed. Macro-averaging calculates the mean value of each metric across all classes, assigning equal importance to normal operation and each fault category. This approach prevents dominant classes from biasing the evaluation results and allows for a more objective comparison of model performance across different fault types.

In addition to classification accuracy, computation time is used to assess the efficiency of each model. Computation time includes both the training time and the inference time, defined as in equations (5), (6), and (7). This metric is essential for evaluating the feasibility of deploying the proposed models in real-time or near real-time diagnostic systems for NEVs, where timely fault detection is a key requirement.

$$T_{train} = t_{end}^{train} - t_{start}^{train} \tag{5}$$

$$T_{test} = t_{end}^{test} - t_{start}^{test} \tag{6}$$

$$T_{total} = T_{train} + T_{test} \tag{7}$$

Where t_{end}^{train} and t_{start}^{train} denote the start and end timestamps of the model training process, respectively, t_{end}^{test} and t_{start}^{test} represent the start and end timestamps of the inference process on the test dataset. T_{train} is the training time and T_{test} is the inference time, and T_{total} is the computation time. All timestamps are recorded in seconds using high-resolution timing functions provided by the MATLAB environment.

Finally, confusion matrix analysis is employed to provide a detailed and intuitive visualization of classification performance. The confusion matrix illustrates the number of correct classifications and misclassifications for each drivetrain operating state, enabling the identification of fault types that are more difficult to distinguish. Normalized confusion matrices are used to better interpret class-level performance and to support a more in-depth discussion of the strengths and limitations of each classification model.

4. RESULTS AND DISCUSSION

4.1. Model Performance Evaluation

Table 1 presents the performance results of three ensemble learning models, namely Random Forest, XGBoost, and CatBoost, evaluated on the NEV fault diagnosis dataset. The reported metrics include classification accuracy, macro-averaged precision, recall, F1 Score, and computation time. All models achieve accuracy values above 99%, indicating that the selected sensor features contain sufficient information to effectively distinguish drivetrain operating states in new energy vehicles.

Table 1. Evaluation results of random forest, xgboost, and catboost.

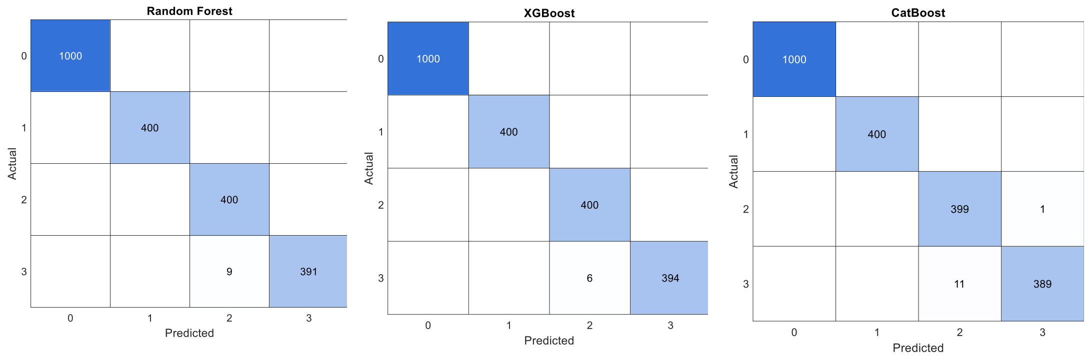
Model	Accuracy (%)	Precision	Recall	F1 - Score	Computation time (s)
Random Forest	99.561	0.994	0.994	0.994	6.1711
XGBoost	99.727	0.996	0.996	0.996	1.5863
CatBoost	99.455	0.993	0.993	0.992	55.1592

Among the evaluated approaches, XGBoost achieves the highest classification performance with an accuracy of 99.727% and precision, recall, and F1 score all equal to 0.996. These results demonstrate that XGBoost provides highly consistent predictions across all fault categories. The class-wise evaluation shows perfect classification for the normal operating condition and Fault 1, while only minor misclassification occurs between Fault 2 and Fault 3. This behavior suggests that XGBoost effectively captures complex nonlinear relationships within the multisensor data.

Random Forest also demonstrates strong diagnostic capability, achieving an accuracy of 99.561% and a F1-Score of 0.994. Similar to XGBoost, Random Forest accurately identifies the normal operating state and Fault 1 with near-perfect performance. However, a slight reduction in recall is observed for Fault 2 and Fault 3, indicating limited confusion between these two fault types. Despite this, the overall balance between precision and recall confirms that Random Forest remains a reliable and robust classification method for multi-class fault diagnosis.

CatBoost achieves an accuracy of 99.455% with a F1-Score of 0.992, which is slightly lower than the other two models. Although CatBoost maintains excellent performance for the normal condition and Fault 1, reduced precision and recall are observed for Fault 2 and Fault 3. This result may be attributed to the nature of the dataset, which consists primarily of continuous numerical features. As CatBoost is particularly effective in handling categorical variables, its advantages are less pronounced in this scenario.

The comparison of computation time reveals clear differences among the models. XGBoost exhibits the most efficient training and inference performance, requiring only 1.586 seconds for training and a negligible inference time per sample. This characteristic makes XGBoost suitable for real-time fault diagnosis and onboard vehicle applications. Random Forest requires a longer training time of 6.171 seconds and exhibits higher inference latency due to the large number of decision trees. CatBoost shows the highest computational cost, with a training time exceeding 55 seconds.



(a) (b) (c)

Fig 3. Confusion Matrix of a) Random Forest, b) XGBoost, c) CatBoost model.

The confusion matrices in **Error! Reference source not found.** indicate that all three models achieve perfect classification for the normal operating condition (label 0) and motor faults (label 1), with all samples correctly identified. Misclassifications are observed only between inverter faults (label 2) and battery faults (label 3). For the Random Forest model, all inverter fault samples are correctly classified, while 9 battery fault samples are misclassified as inverter faults. XGBoost further reduces this confusion, with only 6 battery fault samples incorrectly predicted as inverter faults and perfect classification for inverter faults. In contrast, CatBoost exhibits minor bidirectional confusion, with 1 inverter fault sample misclassified as a battery fault and 11 battery fault samples misclassified as inverter faults. This consistent error pattern across models suggests that the misclassification arises from overlapping sensor characteristics between inverter and battery fault conditions rather than limitations of the learning algorithms. Among the evaluated models, XGBoost demonstrates the most effective fault separation, achieving the lowest misclassification rate while maintaining perfect classification for the remaining fault categories.

4.2. NEVs Drivetrain Faults Diagnosis Demonstration

To demonstrate the deployability of the proposed fault diagnosis framework, a real-time diagnosis workflow was established based on the trained XGBoost model. After the offline training phase, the optimal model was exported and stored together with the corresponding preprocessing parameters, including the mean and standard deviation values used for Z-score normalization. This ensures that incoming operational data is processed consistently with the training stage.

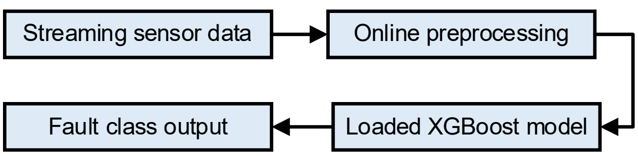


Fig. 4. Fault classification process using streaming sensor data.

In the deployment phase, drivetrain sensor data are assumed to be continuously transmitted from the vehicle to the diagnostic module. Each incoming data sample is first subjected to basic preprocessing, including missing-value handling and normalization using the pre-stored statistical parameters. The processed sample is then fed into the pre-trained XGBoost model, which performs inference without any retraining. The fault category is determined by selecting the class with the highest predicted probability. This sequential processing mechanism enables real-time fault classification while maintaining low computational overhead. In the MATLAB-based simulation, the entire dataset was streamed sample by sample to emulate realworld operating conditions. The system achieved a real-time diagnosis accuracy of approximately 99.5%, with an average inference latency below 1.2 ms per sample.

These results confirm that the proposed approach can be effectively deployed as an online diagnostic module in NEV drivetrain systems, supporting continuous condition monitoring, early fault warning, and predictive maintenance without violating real-time constraints.

5. CONCLUSION

This study evaluated ensemble-based machine learning approaches for drivetrain fault classification in New Energy Vehicles using a structured multi-sensor dataset that represents realistic operating conditions of the electric motor, inverter, and battery system. Random Forest, XGBoost, and CatBoost models were developed and compared in terms of classification accuracy and computational efficiency. The results show that all three models achieve high diagnostic performance, demonstrating the effectiveness of data-driven methods for automated drivetrain fault diagnosis. Among them, XGBoost provides the best trade-off between accuracy and computational cost, making it particularly suitable for real-time and resource-constrained diagnostic applications. Confusion matrix analysis indicates near-perfect classification of normal operation and motor-related faults, while remaining misclassifications mainly occur between inverter-related and battery-related faults due to overlapping sensor characteristics. Overall, the proposed framework supports reliable condition monitoring and fault identification in NEV drivetrain systems. Future work will focus on feature enhancement, parameter optimization, and deployment in practical operating environments to enable predictive maintenance and intelligent health monitoring.

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