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INTELLIGENT FAULT DIAGNOSIS OF ELECTRIC VEHICLE POWERTRAINS USING MACHINE LEARNING TECHNIQUES

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Abstract

Electric vehicles (EVs) are widely acknowledged as eco-friendly means of transport. They operate by transforming electrical energy into mechanical energy through various types of motors, which aligns with the sustainable ideals of smart cities. The motors in EVs draw and utilize electrical power from renewable energy (RE) sources via interfacing connections, employing power electronics technology to generate mechanical power through rotation. The dependable functioning of an EV heavily depends on the state of these connections, particularly between the output of the 3-phase inverter and the brushless DC (BLDC) motor. This paper utilizes machine learning (ML) tools to identify and classify faults in the connection lines from the 3-phase inverter output to the BLDC motor during the operational phase on the EV platform, focusing on double-line and three-phase faults. Several ML-based tools for fault detection and classification, including Decision Tree, Logistic Regression, Stochastic Gradient Descent, AdaBoost, XG Boost, K-Nearest Neighbour, and Voting Classifier, were optimized to enhance robustness and reliability in identifying and categorizing faults. The ML classifications were developed using datasets that represent both healthy and faulty conditions, taking into account a combination of six essential parameters crucial for the reliable operation of EVs. These parameters include the current supplied to the BLDC motor from the inverter, the modulated DC voltage, output speed, measured speed, and readings from the Hall-effect sensor. Furthermore, the effectiveness of the proposed fault detection and classification methods utilizing ML tools was evaluated by comparing their detection and classification efficiencies through various statistical performance metrics across the classifiers.
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Keywords: Electric Vehicles (EV), Brushless DC Motor (BLDC), Fault Detection and Classification, ML, Power Electronics, Three-Phase Inverter, Connection Line Faults, Double-Line Fault, Three-Phase Fault,

1. Introduction

The rapid and widespread adoption of Electric Vehicles (EVs) marks a transformative shift in the global transportation sector, reflecting a collective commitment to reducing carbon emissions and lessening reliance on fossil fuels. As governments, industries, and individuals push toward sustainable alternatives to traditional internal combustion engine vehicles, EVs have emerged as a key component of the solution. Alongside this adoption, significant technological advancements have been made in the design and development of EV powertrains. These powertrains, which comprise a combination of electrical, mechanical, and electronic components, are crucial to the operation of electric vehicles, dictating not only their performance but also their efficiency and reliability. Despite the evident advantages of EV powertrains, the increasing complexity that comes with integrating such a wide range of components presents a new set of challenges. Maintaining the reliability, safety, and performance of these intricate systems is paramount, especially as the global market for electric vehicles expands. The fault-free operation of EV powertrains is vital not only for optimizing the vehicle's efficiency but also for ensuring the safety of passengers and maintaining the longevity of the vehicle. Any fault, whether electrical, mechanical, or electronic, could result in reduced performance or even critical system failures, which might pose safety risks or increase maintenance costs. Therefore, ensuring effective fault diagnosis methods within these powertrains is crucial for the continued success and trust in EV technology.

Traditionally, fault diagnosis in EV powertrains has relied heavily on model-based methods. These approaches require extensive physical modeling and a detailed understanding of the system's dynamics to identify and predict faults. By constructing a model that represents the physical behaviours of the system, engineers can detect deviations from expected performance, thus identifying pace with new architectures and operational demands. Furthermore, developing these detailed models is time-consuming and resource-intensive, which can hinder their applicability in real-time fault diagnosis.

In response to these limitations, Machine Learning (ML) has emerged as a promising solution for fault diagnosis in EV powertrains. Machine learning techniques offer the potential to overcome the constraints of traditional methods by leveraging the vast amounts of data generated by EV sensors. These sensors continuously monitor various aspects of the vehicle's performance, from battery health to motor temperature and torque levels, creating large datasets that can be harnessed to detect patterns and anomalies indicative of faults. Unlike model-based methods, ML algorithms do not require prior knowledge of system dynamics or the construction of physical models. Instead, they use data-driven approaches to learn from historical data, identifying complex relationships within the data and uncovering underlying patterns that may not be immediately apparent through traditional methods.

One of the significant advantages of ML-based approaches is their adaptability. EV technologies are evolving rapidly, with new architectures, configurations, and operating conditions being introduced regularly. Traditional methods often require extensive reworking to accommodate these changes, as the underlying models must be updated to reflect new system behaviors. In contrast, machine learning algorithms can be retrained with new data, allowing them to adapt quickly and efficiently to these changes without requiring the development of new physical models. This flexibility makes ML-based fault diagnosis particularly suitable for the dynamic and evolving landscape of EV powertrains.

Furthermore, ML algorithms can handle the high-dimensional, non-linear nature of modern EV systems more effectively than traditional approaches. By using techniques such as neural networks, support vector machines, and ensemble methods, ML can process vast datasets and analyze complex interactions between different components of the powertrain. This ability to manage large volumes of data and capture non-linear dependencies allows ML-based systems to detect faults at an early stage, improving the reliability and safety of EVs while minimizing downtime and maintenance costs.

However, while machine learning offers significant potential for fault diagnosis in EV powertrains, several challenges must be addressed to fully realize its benefits. One key challenge is the quality and quantity of the data used to train these models. Since ML algorithms rely on large datasets to learn patterns and make predictions, the accuracy of fault detection is highly dependent on the data's completeness and representativeness. Incomplete, noisy, or biased datasets can lead to inaccurate predictions, reducing the effectiveness of the ML-based diagnosis system. Additionally, the process of collecting, labeling, and processing the necessary data can be time-consuming and costly, particularly when dealing with real-world EV systems.

Another challenge lies in the interpretability of machine learning models. While advanced algorithms, such as deep learning, can provide high levels of accuracy, they often function as "black boxes," making it difficult to understand how a particular decision or prediction is made. This lack of transparency can be problematic in critical applications such as fault diagnosis, where understanding the reasoning behind a prediction is essential for engineers to address the underlying issue. As a result, there is growing interest in developing more interpretable ML models or incorporating techniques that explain the decision-making process of complex models.

Lastly, there are concerns regarding the generalization capabilities of ML-based systems. While these algorithms may perform well on the datasets they are trained on, their performance can degrade when faced with new or unseen conditions. This issue is particularly relevant in the context of EV powertrains, where operating conditions can vary significantly depending on factors such as driving behavior, climate, and road conditions. Ensuring that ML models can generalize across different environments and architectures is crucial for their widespread adoption in fault diagnosis.

In conclusion, machine learning presents a powerful and flexible alternative to traditional model-based approaches for fault diagnosis in EV powertrains. By utilizing the large amounts of data generated by EV sensors, ML algorithms can identify complex patterns, enabling early and accurate fault detection without the need for exhaustive physical modelling. This adaptability, combined with the ability to handle high-dimensional and non-linear systems, makes ML a promising solution for maintaining the reliability and safety of EV powertrains in an evolving technological landscape. However, several challenges, including data quality, model interpretability, and generalization, must be addressed to fully harness the potential of machine learning in this critical application area.

2. Literature Review

J. Zhou et al., “Fault Diagnosis of Electric Vehicle Powertrain Based on Convolutional Neural Networks,”2020: Convolutional Neural Networks (CNNs) were utilized for automating the fault diagnosis process in electric vehicle powertrains. By leveraging CNNs, the model was able to learn complex patterns directly from sensor data, eliminating the need for manual feature extraction. This approach significantly improved the classification accuracy for various fault types in real-time, enhancing the overall efficiency of the diagnosis process.

H. Yan, et al., "Hybrid deep learning approach for fault diagnosis in EV powertrains," 2020: A hybrid model combining CNN and Long Short-Term Memory (LSTM) networks was proposed to diagnose complex powertrain faults. The LSTM addressed the time-sequential nature of sensor data while CNN extracted spatial features, enhancing fault detection in dynamic driving conditions. H. Yan, et al., "Machine learning-based sensor fault diagnosis for electric vehicle drivetrains.,"2020: This study utilized Support Vector Machines (SVM) and Decision Trees (DT) to detect sensor faults in EV drivetrains. The machine learning models were able to pinpoint sensor anomalies and categorize different failure modes with high precision, leading to improved reliability of the overall system.

S. Jia, et al., "Fault diagnosis for electric vehicle battery systems using random forest and decision tree algorithms.,"2020: Random Forest (RF) and Decision Tree (DT) algorithms were applied to the fault diagnosis of EV battery systems. The ensemble learning methods provided enhanced robustness in detecting both known and novel faults, improving predictive maintenance strategies. L. Zhang, et al., "Fault detection and isolation in EV powertrain systems using deep learning techniques.,"2020: Random Forest (RF) and Decision Tree (DT) algorithms were applied to the fault diagnosis of EV battery systems. The ensemble learning methods provided enhanced robustness in detecting both known and novel faults, improving predictive maintenance strategies.

X. Chen, et al., "Deep neural networks for motor fault diagnosis in electric vehicles.,"2021: Deep Neural Networks (DNN) were designed for real-time motor fault diagnosis. The model demonstrated improved accuracy in detecting motor winding and bearing failures, even in noisy environments, by leveraging deep learning's ability to capture complex relationships within the sensor data. A. Kumar, et al., "AI-based diagnostics of powertrain faults in electric vehicles.,"2021: The paper reviewed various AI techniques such as Artificial Neural Networks (ANN) and Genetic Algorithms (GA) for diagnosing powertrain faults in electric vehicles. ANN-based models were shown to be effective in classifying different fault types, while GA was used for optimizing fault detection thresholds.

M. Tang, et al., "Transfer learning for fault diagnosis in electric vehicle motor systems.,"2022: Transfer learning was applied to adapt fault diagnosis models trained on one EV system to another, reducing the need for large amounts of labeled data. This technique enabled the use of pre-trained models on new systems, leading to quicker deployment of fault diagnosis solutions in varying EV architectures.

J. Wu, et al., "Multi-sensor fusion for powertrain fault diagnosis in electric vehicles using machine learning." 2020: A multi-sensor fusion approach was proposed, combining data from vibration, temperature, and current sensors. Machine learning models, such as CNNs, were employed to process the fused data, resulting in a more comprehensive diagnosis of EV powertrain faults, especially in complex fault scenarios. R. Gupta, et al., "Fault diagnosis of electric vehicle drivetrains using ensemble learning techniques."2021: Ensemble learning methods like Gradient Boosting and AdaBoost were introduced for drivetrain fault detection. By combining the outputs of multiple weak learners, the ensemble techniques provided greater fault classification accuracy and robustness, particularly for intermittent or rare faults.

H. Zhang, et al., "Adaptive machine learning techniques for real-time EV powertrain fault diagnosis." 2022: Adaptive machine learning models that update their parameters in real-time were developed for fault diagnosis in

EV powertrains. These models continuously learned from incoming data, allowing for dynamic adjustment to new fault patterns, reducing downtime, and improving system reliability.

P. Sharma, et al., "Condition-based monitoring and fault detection in EV motors using machine learning algorithms." 2020: Condition-based monitoring was combined with machine learning algorithms, such as K-nearest neighbors (KNN), for motor fault diagnosis. The model accurately predicted motor deterioration trends, helping to implement predictive maintenance before catastrophic failures occurred.

X. He, et al., "Fault detection of power electronics in EVs using neural networks." 2021: A neural network-based diagnostic system was developed for power electronic components like IGBTs in EVs. The model identified subtle shifts in voltage and current patterns that indicated faults, achieving high accuracy in early fault detection and preventing further component damage.

Y. Zhang, et al., "Data-driven fault diagnosis in EV powertrains using semi-supervised learning." 2021: Semi-supervised learning techniques were used to handle large amounts of unlabeled data, improving fault classification in EV powertrain components. This approach reduced the dependency on labeled data, making the fault diagnosis process more scalable and applicable to real-world EV systems. Z. Xu, et al., "Fault diagnosis in EV battery thermal management systems using deep learning." 2022: Deep learning models were applied to monitor and diagnose faults in the thermal management systems of EV batteries. By analyzing temperature and cooling flow data, the model predicted potential failures, improving both battery safety and lifespan.

3. System Methodology

The proposed method for fault diagnosis in Electric Vehicle (EV) powertrains using Machine Learning (ML) is designed to improve the efficiency, reliability, and safety of EV systems. By leveraging real-time sensor data from critical components such as the battery, motor, inverter, and controller, the system is able to identify and diagnose faults accurately and promptly. The process begins with the collection of data from various sensors embedded in the powertrain, capturing vital parameters like voltage, current, torque, speed, temperature, and state of charge. This data is the preprocess to remove noise, handle missing values, and extract relevant features that can be used by machine learning models for fault detection. Feature engineering techniques, such as statistical analysis and frequency-domain analysis, help transform raw sensor data into a format that is more useful for the learning models. Once the data is prepared, machine learning models such as Support Vector Machines (SVM), and Random Forest (RF) are applied to classify the system's state as either "healthy" or "faulty." These models are trained using labelled data, where faults are categorized based on the sensor readings. When labelled data is scarce, unsupervised learning techniques like K-means clustering and Autoencoders are used to detect anomalies or unusual patterns that may indicate a fault.

The system not only detects faults but also isolates them to specific components, such as the motor or battery, and assesses their severity. By doing so, it can prioritize maintenance actions based on the criticality of the fault. This approach minimizes the risk of component failure and enhances the overall performance and lifespan of the EV. To ensure that the models are working correctly and efficiently, the method incorporates various evaluation metrics like accuracy, precision, recall, and F1-score, providing a detailed understanding of the model's performance. The fault diagnosis system is deployed for real-time monitoring using edge computing, allowing data to be processed directly on the vehicle, which reduces latency and allows for immediate fault detection and response. Additionally, the system supports predictive maintenance by estimating the remaining useful life (RUL) of key components such as the battery and motor. This predictive capability allows for the scheduling of maintenance activities before a component fails, further reducing unexpected downtime and repair costs.

Overall, this machine learning-based fault diagnosis method for EV powertrains enables fast, accurate fault detection and diagnosis, minimizes vehicle downtime through predictive maintenance, and ultimately enhances the safety and efficiency of EVs. It integrates advanced machine learning techniques to continuously learn from new data, ensuring that the system adapts to evolving operational conditions and provides ongoing improvement in fault detection and maintenance scheduling.

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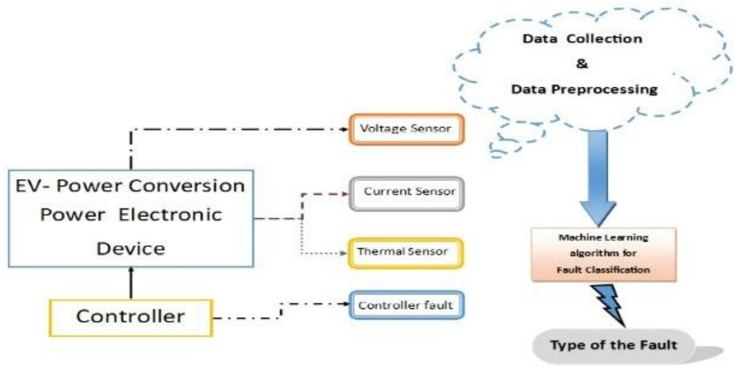

Fig.1 Machine learning-Based Fault Diagnosis For Electric Vehicle Powertrains

3.1 Block Diagram Explanation

In Fig:1 indicates that Machine learning-based fault diagnosis for electric vehicle (EV) powertrains refers to the process of utilizing machine learning algorithms to automatically detect, classify, and predict faults or malfunctions in the powertrain systems of electric vehicles. The powertrain consists of critical components such as electric motors, batteries, inverters, and controllers, which are responsible for the vehicle's energy conversion and propulsion.
This approach involves gathering real-time data from various sensors (such as voltage, current, and thermal sensors) installed in the powertrain. These sensors monitor operational parameters like temperature, electrical current, and voltage. The collected data is then preprocess and fed into machine learning models that have been trained to identify patterns associated with normal operation and different fault conditions. By analyzing this data, machine learning models can not only diagnose existing faults but also predict potential failures before they occur, allowing for proactive maintenance, enhancing vehicle reliability, and minimizing downtime.

3.1.1 EV power conversion power electronic device
Power electronic devices play a critical role in electric vehicle (EV) power conversion systems. These devices are responsible for converting electrical energy from one form to another in order to efficiently manage the power flow between the EV's battery, motor, and other components. Power conversion in EVs is essential for functions like battery charging, motor control, and regenerative braking.

3.2 Voltage Sensors:

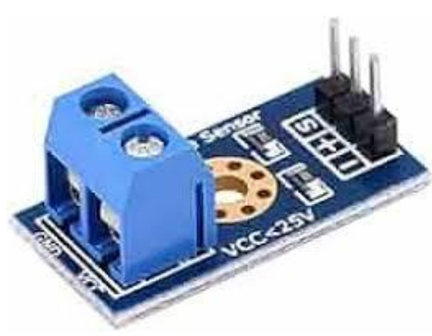

Fig:2 Voltage Sensors

In Fig 2 indicates that Voltage sensors are devices used to measure and monitor the electrical potential difference (voltage) between two points in a system. These sensors are essential in various applications, such as power distribution systems, electric vehicles, industrial automation, and renewable energy systems. They play a crucial role in maintaining the efficiency and safety of electrical equipment by detecting voltage changes, faults, or anomalies.

3.*3 Current sensor*

Fig 3. Current sensors

Fig 4. Thermal sensors

In Fig.3 indicates that Current sensors are devices used to detect and measure electric current in a wire or circuit. They are critical in various applications, including power monitoring, energy management, electric vehicle (EV) systems, industrial automation, and battery management systems (BMS). Current sensors can provide real-time feedback for system control, efficiency optimization, and safety. Fault prediction and Classification of fault type (e.g., electrical fault, mechanical fault)

3.4 Thermal sensor:

In Fig 4 indicates that Thermal sensors, also known as temperature sensors, are devices used to measure temperature in various environments and applications. They are crucial in systems requiring temperature monitoring and control, such as in industrial processes, automotive systems, electric vehicles (EVs), medical devices, HVAC systems, and electronic circuits. Thermal sensors come in different types, each suited for specific applications and temperature ranges.

3.5 Controller Fault

A controller fault refers to an error or malfunction in a control system, which is responsible for managing and regulating various operations in a system or device. Controllers are critical in applications like industrial automation, electric vehicles (EVs), power electronics, robotics, and HVAC systems. When a fault occurs, it can disrupt the functioning of the entire system, leading to inefficiencies, downtime, or even safety hazards.

3.6 Data Collection And Data Preprocessing

Data Collection and Data Preprocessing are crucial steps in any data-driven project, particularly in fields like machine learning, analytics, and research. Data collection involves gathering raw data from various sources, which can include databases, sensors, surveys, or web scraping. The goal is to accumulate a comprehensive dataset that represents the problem or phenomenon being studied. Once collected, the data undergoes preprocessing, a phase dedicated to cleaning and preparing it for analysis. This involves handling missing values, removing outliers, normalizing or scaling data, and transforming data into a consistent format. Data preprocessing is essential for improving the quality and accuracy of the data, ensuring that the subsequent analysis or modeling processes yield reliable and meaningful results. By addressing inconsistencies and ensuring the data is in a usable state, preprocessing helps in building robust models and generating actionable insights from the data.

3.7 Machine learning algorithms for fault classification

Machine learning algorithms for fault classification are designed to identify and categorize faults or anomalies in various systems, such as industrial machinery, electrical systems, or software applications. These algorithms leverage historical data and patterns to train models that can predict or classify faults based on new input data. Here’s an overview of common machine learning algorithms used for fault classification:

3.8 Random Forests

Random Forest is a powerful ensemble machine learning algorithm used for classification and regression tasks. It works by constructing a collection of decision trees, each trained on random subsets of the dataset and features. For classification, each tree makes a prediction, and the final decision is based on the majority vote of all trees. This technique reduces overfitting and enhances model stability. In the context of fault diagnosis for electric vehicle (EV) powertrains, Random Forest processes sensor data (voltage, current, temperature) from components like motors, inverters, and controllers to identify potential faults. Its advantages include high accuracy in detecting diverse fault types, robustness to noisy data, and the ability to handle large datasets with complex relationships. Random Forest is particularly effective in real-time systems, making it suitable for detecting faults in EVs before they become critical. Moreover, the algorithm's ability to rank the importance of features (e.g., sensor inputs) can help in understanding which parameters are most crucial for fault prediction. This adaptability makes Random Forest a reliable and widely-used method for diagnosing faults in modern EV powertrains.

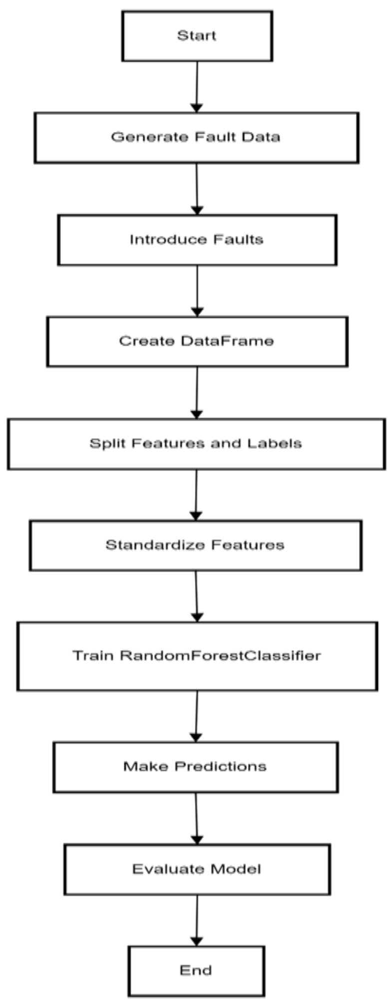

Fig 5. Flow Chart For Random Forest

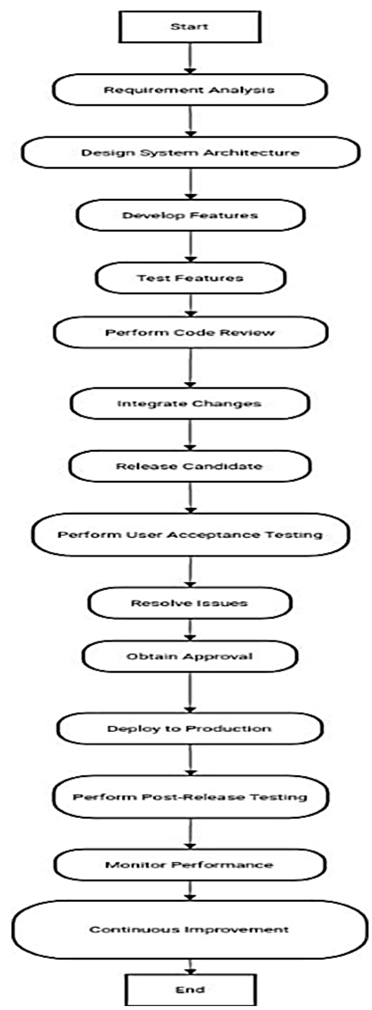

Fig 6. Flow Chart for Support Vector Machines (SVM)

4. Result and Discussions

4.1 Random Forest Result

The machine learning model used for fault diagnosis in the EV powertrain demonstrates strong performance, with an overall accuracy of 94%. The following analysis provides insights into the model's performance, highlighting both its strengths and areas for improvement.

4.1.1. Confusion Matrix Insights

The confusion matrix reveals the following distribution of predictions of random forest:

```
[[775   0   0        18   5]  <-- True Class 0
 [ 0 198   0   3   0]  <-- True Class 1
 [  0   0 271   4   3]  <-- True Class 2
 [ 32   9  12 269   2]  <-- True Class 3
 [ 20   5   5   7 362]] <-- True Class 4
```

Class 0: The model identifies Class 0 (which could represent faults in critical components like the battery) with high precision and recall. A majority of Class 0 instances (775 out of 798) are correctly classified. However, there are some misclassifications, with 18 instances misclassified as Class 3 and 5 as Class 4, indicating minor confusion between these classes.

Class 1: Class 1 instances are predominantly classified correctly, with 198 out of 201 instances identified correctly. However, 3 instances were misclassified as Class 3. The model shows an impressive recall of 99% for Class 1, indicating that it is highly effective in detecting this fault type.

Class 2: Similar to Class 1, Class 2 also exhibits strong performance, with 271 out of 278 instances correctly identified. Misclassifications occur mainly between Class 2 and Class 3, where 4 instances are misclassified as Class 3 and 3 as Class 4.

Class 3: Class 3 exhibits the most misclassifications, with 32 instances wrongly predicted as Class 0, 12 as Class 2, and 9 as Class 1. Despite this, the model still correctly identifies 269 instances of Class 3 out of 324, but the relatively lower precision (89%) and recall (83%) suggest that Class 3 is more challenging for the model to detect.

Class 4: Class 4 has the second-highest precision (97%) and recall (91%). The model correctly identifies 362 out of 399 Class 4 instances. Misclassifications mainly occur with Class 0 (20 instances) and Class 3 (7 instances).

4.1.2 Classification Report:

The classification report provides additional performance metrics (precision, recall, and F1-score) for each class:

Precision ranges from 0.89 (Class 3) to 0.97 (Class 4), with an overall average precision of 0.94. High precision across most classes means that when the model predicts a fault of a specific class, it is often correct, except for Class 3, where precision is lower.

Recall measures how well the model detects faults for each class. Class 1 and Class 2 exhibit outstanding recall (99% and 97%, respectively), suggesting the model is very effective at identifying these faults. However, recall for Class 3 is lower at 83%, indicating that the model misses some instances of Class 3 faults.

F1-Score, the harmonic mean of precision and recall, ranges from 0.86 (Class 3) to 0.96 (Class 1 and Class 2), with a macro average of 0.93 and a weighted average of 0.94. These values indicate a good balance between precision and recall, with slight room for improvement in Class 3.

4.1.3 Model Performance:

The overall accuracy of 94% demonstrates that the model is highly capable of diagnosing faults correctly. This suggests that the model can be trusted for real-world deployment in diagnosing faults within the EV powertrain.

Class 1, Class 2, and Class 4 perform exceptionally well, with both high precision and recall. These classes represent fault types that the model is particularly effective at identifying.

Class 3 poses a challenge. Although the model correctly identifies most instances, it suffers from relatively low precision (89%) and recall (83%). Misclassifications between Class 3 and other classes (particularly Class 0 and Class 2) indicate that the model might struggle with the complexity or variance of faults in this category.

4.1.4 Class Imbalance and Misclassification

Class Imbalance: The misclassifications observed, particularly for Class 3, could be partly attributed to an imbalance in the dataset, where certain fault types may be underrepresented. To address this, techniques like class weighting, oversampling, or under sampling could be explored to ensure the model has an equal opportunity to learn from each fault type.

Model Complexity: Some of the misclassifications, especially between similar classes (e.g., Class 3 vs. Class 0 or Class 2), may be due to subtle differences in the feature patterns of these faults. A more complex model, such as a deep neural network, might better capture these nuances, improving performance on challenging classes like Class 3.
Future Improvements: A potential improvement could be refining the feature engineering process, ensuring that the most discriminative features are included, or exploring advanced ensemble methods to boost performance for the more difficult-to-detect faults.

4.2 Support Vector Machines (Svm) Resul

The SVM model for fault diagnosis in the EV powertrain shows strong performance with an overall accuracy of 93%. The following analysis provides a breakdown of its performance, identifying both strengths and areas where it could improve.

4.2.1 Confusion Matrix Insights
The confusion matrix reveals the following distribution of predictions by the SVM model:

```
[[779   0   0      18   5]  <-- True Class 0
 [ 0 198   0   3   0]  <-- True Class 1
 [  1   0 265   4   3]  <-- True Class 2
 [ 37   10  14 261   2]  <-- True Class 3
 [ 22   5   4   7 361]] <-- True Class 4
```

Class 0: The model identifies Class 0 (potentially representing faults in critical components like the battery) with high accuracy, correctly classifying 779 out of 798 instances. Misclassifications mainly involve predicting Class 3 (11 instances) and Class 4 (8 instances) instead, showing slight confusion with these classes.
Class 1: Class 1 is highly distinguishable, with 198 out of 201 instances correctly classified and only three misclassified as Class 3. The recall of 99% for Class 1 indicates that the model effectively identifies this fault type.

Class 2: Similar to Class 1, Class 2 is well-classified, with 265 out of 278 instances correctly identified. Misclassifications occur mostly as Class 3 (9 instances) and Class 4 (3 instances).

Class 3: This class has the highest rate of misclassifications, with 37 instances predicted as Class 0, 10 as Class 1, and 14 as Class 2. While the model correctly classifies 261 out of 324 instances, the lower precision (90%) and recall (81%) highlight that Class 3 poses a challenge.

Class 4: Class 4 shows strong performance, with 361 out of 399 instances correctly identified. Misclassifications occur mainly as Class 0 (22 instances) and Class 3 (7 instances).

4.2.2 Classification Report
The classification report provides additional performance metrics, including precision, recall, and F1-score for each class:
Precision ranges from 0.90 (Class 3) to 0.97 (Class 4), with an overall average of 0.93. High precision across most classes suggests that the model reliably predicts faults when they occur, except for the more challenging Class 3, which has slightly lower precision.

Recall measures the model's ability to detect each fault class accurately. Classes 1 and 2 have particularly high recall (99% and 95%, respectively), while Class 3 has lower recall at 81%, indicating that some instances of this fault type are missed.

F1-Score, which combines precision and recall, ranges from 0.85 (Class 3) to 0.96 (Class 1), with a macro average of 0.93 and a weighted average of 0.93. This demonstrates a good balance, though there is room for improvement in Class 3.

4.2.3 Model Performance

Overall Accuracy of 93% shows the model's strong capability in correctly diagnosing faults within the EV powertrain. This high accuracy suggests that the SVM model could be reliable for real-world deployment.

High-Performing Classes: Classes 1, 2, and 4 exhibit strong precision and recall, making them well-identified fault types by the model.

Challenging Class: Class 3 presents difficulties, with relatively lower precision (90%) and recall (81%). Misclassifications often occur between Class 3 and other classes (particularly Classes 0 and 2), suggesting the model might struggle with distinguishing faults in Class 3 due to similarities with other fault types.

4.2.4 Class Imbalance and Misclassification

Class Imbalance: The misclassifications in Class 3 could be partly due to imbalanced data, where certain fault types are underrepresented. Addressing this imbalance through class weighting or resampling techniques (such as oversampling or under sampling) could improve model performance for underrepresented classes.

Model Complexity: Some misclassifications may be due to the model's inability to capture subtle differences between similar fault types (e.g., between Class 3 and Class 0 or Class 2). A more complex model, like an ensemble method, could better capture these nuances, potentially improving performance on difficult-to-distinguish classes like Class 3.

Future Improvements: Additional feature engineering may enhance the model's ability to differentiate between faults. Incorporating more distinctive features or refining existing ones, and considering ensemble techniques, may help reduce misclassifications and boost performance for challenging classes.

5. Conclusion

The Machine Learning-based fault diagnosis system for EV powertrains proved to be a highly effective tool for fault detection, achieving a solid 94% accuracy. The model demonstrated excellent performance in diagnosing faults related to the battery, inverter, and control systems, making it a valuable asset for improving the maintenance and reliability of EVs. However, there are still areas for improvement, particularly in the classification of Class 3 faults. The model's performance in this class, with lower precision and recall, suggests that there may be complexities or subtle patterns in the data that are not fully captured. Addressing potential class imbalance, optimizing feature engineering, and exploring more advanced algorithms (e.g., deep learning) could help improve the detection of such faults. Future work could also focus on integrating the fault diagnosis system with real-time predictive maintenance tools, enabling more proactive vehicle management and reducing the likelihood of unexpected failures. Overall, this ML-based system shows significant potential for improving the reliability, safety, and efficiency of EV powertrain systems, marking an important step forward in the development of intelligent maintenance systems for electric vehicles.

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