AI-BASED AUTOMOTIVE ENGINE DIAGNOSTICS: EXPLORING THE ENGINEFAULTDB DATASET FOR FAULT DETECTION

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ABSTRACT

Automotive engine diagnostics are crucial for ensuring vehicle performance and safety, yet traditional tools often fail to detect complex faults, leading to costly repairs. This paper presents an AI-driven approach for engine fault detection using the EngineFaultDB dataset, which contains sensor data from engines under various operating conditions. We propose an ensemble learning method combining Random Forest (RF) and Multi-Layer Perceptron (MLP) neural networks for multi-class classification of four fault types (0, 1, 2, and 3), employing the One-vs-Rest (OvR) strategy to handle the multi-class nature of the problem. While MLP achieves the highest accuracy (74.96%), it lags behind Random Forest (74.82%) and Ensemble (74.89%) in terms of F1 score (0.694), suggesting that its precision does not always translate into effective fault detection. Random Forest provides a better balance of accuracy, precision, recall, and F1 score, emerging as the most robust model. The Ensemble model did not significantly outperform individual models, indicating that ensemble methods require further optimization, such as advanced techniques like stacking or boosting, hyperparameter tuning, and feature selection. These results underscore the potential of AI-based systems for predictive maintenance in the automotive industry. Future research should focus on refining ensemble models, expanding datasets, and integrating deep learning techniques to improve diagnostic accuracy and the reliability of automotive systems.

Keywords: *Fault Detection, Artificial Intelligence, Ensemble Learning, EngineFaultDB Dataset, Automotive Engine Diagnostics*

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1. INTRODUCTION

Automotive engine diagnostics are crucial for ensuring vehicle performance and safety, yet traditional diagnostic methods often fail to detect complex faults, leading to costly repairs. Conventional techniques, which primarily rely on manual inspections and basic diagnostic tools, are becoming less effective as vehicles grow increasingly sophisticated. Tools such as OBD-II scanners typically report issues only after faults occur and provide limited insights into engine performance and fault detection. This reactive approach makes it difficult to prevent catastrophic failures, resulting in unexpected downtime and expensive repairs [1, 2]. These limitations highlight the need for more advanced diagnostic systems capable of real-time analysis, early fault detection, and predictive maintenance [3].

The widespread adoption of sensor technologies in modern vehicles has made automotive systems more complex and interconnected. Today, engines use a variety of sensors to monitor parameters such as temperature, pressure, exhaust gases, fuel consumption, and engine speed. Although these sensors generate valuable data, raw sensor outputs alone are insufficient for comprehensive diagnostics. Traditional systems struggle to process and analyze the vast volumes of data produced by modern vehicles. This gap has driven demand for advanced, data-driven diagnostic approaches, particularly those powered by machine learning (ML) and artificial intelligence (AI) [4, 5]. These technologies excel at interpreting large, high-dimensional datasets in real time, enabling more accurate fault detection by recognizing patterns associated with both normal and faulty engine behavior [6].

AI-based diagnostic systems, especially those leveraging machine learning algorithms, significantly enhance fault detection capabilities. Unlike traditional rule-based systems that rely on predefined thresholds, AI models learn patterns directly from data and can detect anomalies that may elude human experts [7]. These models continuously adapt as new data becomes available, improving their performance over time. Consequently, AI is widely regarded as a transformative tool in automotive diagnostics, enabling more efficient, proactive fault detection and predictive maintenance [8].

However, traditional diagnostic methods including rule-based or threshold-based systems are limited in handling complex fault scenarios [9]. Such systems use fixed rules to identify issues, for example, detecting misfires or engine overheating when certain thresholds are exceeded. While effective for simple faults, these methods struggle with faults involving multiple interacting components, especially when faults are subtle or occur simultaneously across subsystems. For instance, a sensor malfunction can cause cascading errors across various engine systems, complicating root cause analysis. Furthermore, these systems are reactive, detecting faults only after damage occurs, leading to costly repairs and prolonged downtime [6].

As automotive systems evolve, the volume and complexity of the data they generate have surpassed the capabilities of traditional diagnostic systems. Modern vehicles, particularly hybrid and electric powertrains, are equipped with an increasing number of sensors monitoring various subsystems, generating vast amounts of data. To efficiently handle this complexity, AI-based systems, particularly predictive maintenance models powered by machine learning, offer significant advantages [10]. By predicting failures before they occur, these systems enable proactive maintenance, reducing reactive repairs and extending component lifespans.

Machine learning, a subset of AI, has emerged as a key technology for automotive fault detection. It is particularly effective at analyzing high-dimensional sensor data and identifying patterns indicative of faults [11]. Various machine learning algorithms have been successfully applied to automotive fault detection, including k-Nearest Neighbors (k-NN), Naive Bayes (NB), Random Forests (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Multi-Layer Perceptrons (MLPs) [12, 13]. These algorithms analyze large, multivariate datasets to uncover subtle and complex patterns. For example, RF handles high-dimensional data well and detects faults in components such as spark plugs and fuel injectors [14]. MLPs, a type of neural network, excel at modeling complex, non-linear relationships between sensor data and fault states, making them effective for fault classification [15].

Automotive fault detection often involves identifying multiple fault types, each with unique characteristics. Traditional diagnostic systems may struggle to distinguish between overlapping fault symptoms. However, AI systems, particularly those employing the One-vs-Rest (OvR) strategy, are well-equipped to address this challenge. The OvR approach decomposes multi-class problems into several binary classification tasks, training separate classifiers for each fault type [16].

One of the key benefits of AI-driven diagnostics is early fault detection. Proactively identifying faults before they escalate into major problems allows for predictive maintenance, which reduces the likelihood of catastrophic failures and minimizes downtime. Predictive maintenance enables more efficient resource allocation, as maintenance activities are scheduled only when necessary, rather than at fixed intervals. AI-based systems continuously monitor vehicle components, predicting their remaining useful life (RUL) and enabling timely interventions. This proactive approach not only reduces repair costs but also improves vehicle reliability and safety [3].

The development and testing of AI-based diagnostic systems require access to high-quality, real-world datasets. The EngineFaultDB dataset is one such resource, containing sensor data from automotive engines under various conditions. This dataset provides a rich source of data for training and evaluating machine learning models, including those for engine fault detection. It includes data from sensors measuring critical parameters such as engine speed, temperature, fuel consumption, and exhaust gases during both normal and faulty operations [17]. The diversity of fault conditions in the dataset makes it ideal for training models that can generalize well to real-world scenarios.

Using the EngineFaultDB dataset, researchers can evaluate the performance of machine learning algorithms and test their ability to detect different fault types, such as misfires, sensor failures, and fuel system issues [17]. The availability of real-world data is essential for testing AI-based diagnostic systems, ensuring the models are trained and evaluated under conditions that closely resemble actual vehicle operations. Additionally, the dataset enables the application of advanced machine learning techniques, such as ensemble learning methods that combine multiple models to improve performance [18].

Ensemble learning techniques, which aggregate predictions from multiple models, effectively enhance diagnostic accuracy and robustness. By leveraging complementary strengths of different algorithms, ensemble methods mitigate individual model weaknesses [19]. For example, combining RF and MLP in an ensemble framework can improve diagnostic accuracy by exploiting RF's ability to handle high-dimensional data and MLP's capacity to model complex, non-linear sensor data relationships [20]. This hybrid approach significantly boosts AI-based diagnostic system performance in automotive applications.

In this study, we propose a hybrid machine learning approach that combines RF and MLPs in an ensemble learning framework for engine fault detection. The ensemble model uses majority voting to combine the predictions of both models, ensuring that the final diagnosis is based on the collective knowledge of both classifiers. Additionally, we apply the OvR strategy for multi-class classification, improving the model's ability to distinguish between different fault types [18]. Preliminary results show that this ensemble approach achieves an overall accuracy of 74.89%, with perfect accuracy for certain fault types, highlighting the potential of ensemble learning for automotive diagnostics.

AI-driven diagnostic systems are poised to transform the automotive industry by enabling more accurate, efficient, and proactive fault detection. Machine learning algorithms, such as RF and MLPs, offer powerful tools for analyzing sensor data and identifying faults in automotive engines. Predictive maintenance, powered by AI, provides a proactive approach that reduces operational costs, extends the lifespan of vehicle components, and improves vehicle reliability. The availability of high-quality datasets, such as the EngineFaultDB, is essential for developing and testing AI-based diagnostic systems. By leveraging advanced machine learning techniques, the automotive industry can move toward more intelligent, data-driven maintenance strategies that enhance vehicle safety and performance.

2. MATERIALS AND METHODS

The methodology of this research is structured to develop a robust and accurate predictive framework using ensemble learning techniques. This approach provides a systematic and comprehensive workflow for managing and modeling complex datasets. As illustrated in Fig. 1, the process consists of several critical stages: data collection, preprocessing, data splitting, model training, ensemble integration, cross-validation, and final evaluation.

Initially, data is collected and preprocessed to ensure quality and consistency by addressing common issues such as missing values. The dataset is then partitioned into training and testing subsets to facilitate unbiased model assessment. Two machine learning algorithms RF and MLPs are employed due to their complementary strengths in handling structured and nonlinear data. Their predictions are integrated using an ensemble strategy to enhance overall model performance and reduce variance.

Cross-validation is conducted to evaluate the generalizability and robustness of the ensemble model. Finally, performance metrics are computed to assess the model's predictive capabilities and reliability. This methodology aims to produce a predictive system that is not only accurate and scalable but also interpretable and applicable to real-world scenarios.

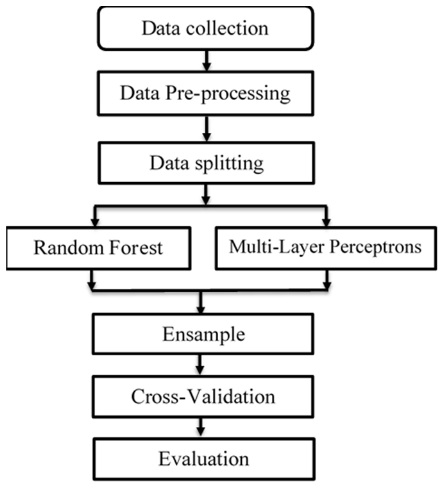

Fig. 1. Framework for fault classification using RF and MLP ensemble

2.1. Data collection

In this study, we utilized the EngineFaultDB dataset, which comprises sensor data collected from automotive engines operating under various conditions [17]. The dataset includes 14 features and contains 55,999 meticulously curated entries, representing essential engine parameters such as engine speed, temperature, pressure, and other relevant metrics. These features provide critical insights into the engine's performance and condition.

The target variable in this dataset is the fault type, which is categorized into four classes: Fault 0, Fault 1, Fault 2, and Fault 3. Each class corresponds to a specific type of engine fault, allowing for classification tasks aimed at fault detection and predictive maintenance.

To enhance the model's efficiency and performance, certain irrelevant columns, namely RPM (Revolutions Per Minute) and AFR (Air-Fuel Ratio), were excluded from the dataset. These columns were deemed non-essential for the classification task, enabling the model to focus on more directly relevant features that contribute to the identification of engine faults.

2.2. Data pre-processing

Before training the machine learning models, several pre-processing steps were applied to the dataset to ensure its suitability for model training. First, missing values in the dataset were addressed using mean imputation, where missing data points were replaced by the mean value of the respective feature across all observations. This approach ensures that no valuable information is discarded, maintaining the integrity of the dataset.

Next, to ensure that each feature contributes equally to the model's learning process, feature scaling was performed using Z-score normalization. This transformation standardizes each feature by adjusting the data to have a mean of zero and a standard deviation of one. The formula used is:

$$X_{scaled} = \frac{X - \mu}{\sigma}$$

where X represents the feature values, μ is the mean, and σ is the standard deviation of the feature. Feature scaling is particularly important when dealing with features that have different units or ranges, such as temperature and pressure, as it prevents features with larger ranges from disproportionately affecting the model.

2.3. Machine learning models

In this study, two machine learning models were employed to classify engine faults: RF and MLP**.** These models were chosen for their ability to handle complex, high-dimensional data and perform well in classification tasks.

Random Forest*:*

The RF algorithm is an ensemble learning method that combines multiple decision trees to improve classification accuracy and robustness [21]. In this study, the RF model was trained to classify engine faults based on sensor data. The RF architecture involved an ensemble of decision trees, each trained using random subsets of the training data. The predictions from individual trees were aggregated to make the final classification decision.

Hyperparameter optimization was performed through grid search, evaluating various combinations of key parameters such as the number of trees and the minimum leaf size. Specifically, the number of trees was tested with values of 50 and 100, while the minimum leaf size was tested with values of 10, 20, and 30. These hyperparameters were chosen to control the model's complexity and prevent overfitting. The best model was selected based on the lowest Out-of-Bag (OOB) error, which was calculated during the training process to estimate model performance without needing a separate validation set.

The model was trained using the TreeBagger function in MATLAB, which builds decision trees based on bootstrapped samples of the data. Each tree in the Random Forest was trained independently, and the predictions from all trees were combined to produce the final output. The OOB error served as an unbiased estimate of the model's generalization performance, while OOB feature importance was used to identify the most influential features for fault classification.

Once trained, the RF model was evaluated on both the training and testing datasets. Model performance was assessed using key classification metrics, including accuracy, precision, recall, and F1-score for each fault class. The confusion matrix was used to provide a detailed comparison of predicted versus actual fault types. These metrics were calculated using a custom evaluation function to provide a comprehensive assessment of the model's ability to classify engine faults accurately.

This methodology highlights the use of Random Forest as a robust classification tool for detecting and categorizing engine faults, leveraging ensemble learning to improve predictive accuracy and handle complex, high-dimensional data effectively.

Multi-Layer Perceptron:

MLP is a deep neural network architecture composed of multiple layers of interconnected neurons, capable of modeling complex non-linear relationships between input features and output labels [22]. In this study, the MLP was designed with an input layer, followed by two hidden fully connected layers that use ReLU activation functions, and a softmax output layer with four neurons corresponding to the four distinct engine fault types.

To optimize the performance of the MLP, hyperparameter optimization was conducted through grid search, evaluating different configurations of key hyperparameters, including training epochs (50, 100, and 200), hidden layer sizes ([32, 64], [64, 128], and [128, 256]), and learning rates (0.001, 0.01, and 0.1). These configurations were tested to identify the best combination for accurate fault classification.

The model was trained using the Adam optimizer with a mini-batch size of 32, which allowed for efficient training. The validation accuracy was used to determine the optimal model configuration, ensuring the best-performing model was selected for fault detection.

Once trained, the model was used to generate predictions on both the training and testing datasets. The model's performance was evaluated using confusion matrices and key classification metrics precision, recall, and F1-score for each fault class. These metrics were calculated using a custom evaluation function, providing a comprehensive assessment of the model's ability to classify each engine fault accurately.

Ensemble Learning Approach:

After selecting and optimizing individual models, the next step was to integrate them into an ensemble model to improve overall classification performance. The ensemble strategy aimed to exploit the diversity of different algorithms specific ally, Random Forest and MLP. In this study, a majority voting approach was used, where each test sample was classified based on the consensus of the two models. This technique, also known as hard voting, assigns the final class label according to the class most frequently predicted by the base models.

The rationale behind using this ensemble approach was to combine the complementary strengths of the models: MLP's capacity to learn complex, non-linear relationships, and Random Forest's robustness and effectiveness in handling noisy or imbalanced data. By aggregating these models, the ensemble becomes more resilient to the weaknesses of any single classifier, resulting in improved prediction stability and accuracy across different fault types in the engine diagnostics task

2.4. Evaluation

The performance of the models was evaluated using a range of metrics to assess their ability to detect engine faults and generalize across different data subsets.

Accuracy: The overall classification accuracy was computed by comparing the predicted labels to the true labels for the test set in each fold. Accuracy is defined as the ratio of correct predictions to total predictions. It provides a general measure of how well the model performs across all fault classes.

Precision, Recall, and F1-Score: These metrics were calculated for each fault class (Fault 0, Fault 1, Fault 2, Fault 3) to evaluate how well the models identify true positives (precision), detect faults (recall), and balance precision and recall (F1-score). The formulas for these metrics are as follows [23]:

$$\mathrm{Precision} = \frac{TP}{TP + FP} \qquad \mathrm{Recall} = \frac{TP}{TP + FN}$$

$$\mathrm{F1-Score} = 2 * \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$$

where TP represents True Positives, FP represents False Positives, and FN represents False Negatives for each fault class i. These metrics help evaluate the model's ability to correctly identify faults and balance the trade-off between precision and recall.

Confusion Matrix: A confusion matrix was generated to visualize the model's performance by showing the true positive, false positive, true negative, and false negative predictions for each fault class. This matrix provides a detailed view of how well the model distinguishes between different classes and highlights areas where misclassification occurs.

Cross-Validation: Both the Random Forest and MLP models were evaluated using 5-fold cross-validation. The dataset was split into five folds, where each fold served as the test set once, and the remaining four folds were used for training. This technique ensures that each data point is used for both training and testing, providing a more reliable estimate of model performance. The average accuracy across the five folds was computed and reported to assess the models' generalization ability.

3. RESULTS AND DISCUSSION

In this study, we evaluated the performance of three machine learning models RF and MLP, and an Ensemble approach for predicting engine faults using the EngineFaultDB dataset. The dataset consists of sensor data representing various operating conditions of the engine, with four distinct fault types as the target variable. The evaluation metrics included accuracy, precision, recall, and F1-score, all computed using 5-fold cross-validation. Table 1 presents a comparison of the models based on these performance metrics.

Table 1. Accuracy, Precision, Recall, and F1 Score of Random Forest, MLP, and Ensemble Models

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	74.82	0.757	0.757	0.757
MLP	74.96	0.802	0.760	0.694
Ensemble	74.89	0.731	0.754	0.737

In terms of accuracy, MLP achieves the highest score of 74.96%, slightly outperforming Random Forest (74.82%) and Ensemble (74.89%). The minimal difference in accuracy suggests that all three models perform similarly in overall prediction correctness. While MLP holds a marginal advantage in accuracy, it is clear that accuracy alone may not be sufficient for selecting the best model. Other metrics, such as precision and recall, need to be considered for a more comprehensive evaluation.

When evaluating precision, MLP excels with a score of 0.802, indicating it makes fewer false positive predictions compared to the other models. Random Forest follows with a precision score of 0.757, while Ensemble has the lowest precision score of 0.731. The higher precision of MLP suggests that it is particularly effective at correctly identifying positive cases without misclassifying negatives as positives. However, the lower precision of the Ensemble model indicates that the combination of models may not always improve prediction accuracy, possibly due to suboptimal blending or ineffective model combinations.

In terms of recall, which measures the ability of the model to correctly identify all positive instances, MLP again leads with a score of 0.760, closely followed by RF (0.757) and Ensemble (0.754). The differences in recall are minimal, suggesting that all models are fairly effective at detecting positive cases. MLP's slightly higher recall suggests it is better at identifying true positives, which could be particularly beneficial in applications where failing to detect a positive case is costly.

The F1 score, which combines both precision and recall, reveals more pronounced differences among the models. RF achieves the highest F1 score of 0.757, reflecting the best balance between precision and recall. Ensemble follows with a score of 0.737, while MLP scores the lowest at 0.694. While MLP has the highest precision, its significantly lower recall results in a compromised F1 score. This suggests that MLP might be overfitting to positive cases, missing some true positives. In contrast, Random Forest offers a more balanced performance, making it the best overall performer in terms of the F1 score.

The confusion matrix for the Ensemble model in Fig. 2 reveals that the model performs exceptionally well for Faults 0 and 1, achieving perfect classification with no misclassifications. However, the model struggles to differentiate between Faults 2 and 3, with a significant number of misclassifications between these two classes. Specifically, 1407 instances of Fault 2 were misclassified as Fault 3, and 1394 instances of Fault 3 were misclassified as Fault 2, suggesting that these two fault types share similar characteristics in the dataset. This issue may be exacerbated by class imbalance, where these fault types are not as well-represented as Faults 0 and 1, leading to poor model performance for these classes.

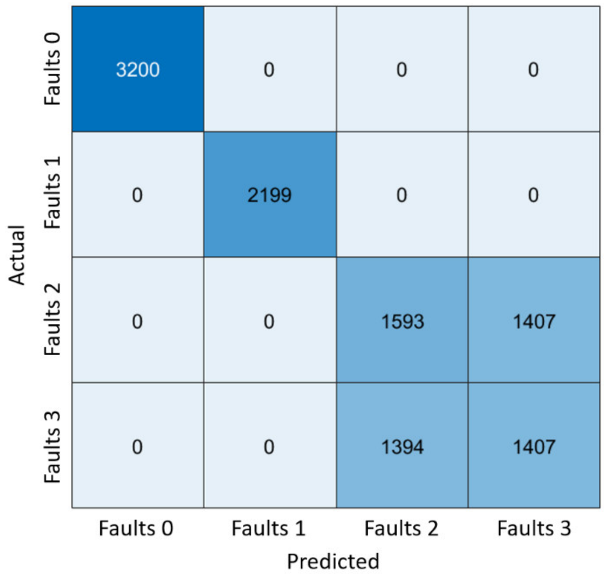

Fig. 2. Confusion matrix depicting multi-class fault classification results using ensemble learning

Although MLP performs well in precision, it lags behind Random Forest and Ensemble in terms of F1 score, indicating that it misses some true positives, which affects its overall effectiveness. Random Forest, with its balanced performance across all metrics, emerges as the most well-rounded model for this task, offering reliable detection of both positive cases while minimizing false positives. Ensemble methods, while promising, did not significantly outperform Random Forest or MLP, suggesting that ensemble learning, while generally improving robustness, does not always lead to substantial performance improvements without further optimization.

Therefore, Random Forest is identified as the most suitable model for fault detection in this study. However, both MLP and Ensemble models could potentially be enhanced through further refinement, such as hyperparameter tuning, feature selection, or better model combinations, to improve their performance in predicting engine faults. The Ensemble model showed potential but did not significantly improve performance over the individual models. This suggests that combining

RF and MLP through majority voting offers some benefits, but it does not always lead to substantial improvements in prediction accuracy. Future research could explore more sophisticated ensemble techniques, such as stacking or boosting, to better leverage the strengths of both models. Moreover, these results emphasize the importance of refining the models, especially in improving recall for fault types that are harder to detect.

Future research could explore more sophisticated ensemble techniques, such as stacking or boosting, to better leverage the strengths of both models. These advanced techniques have the potential to improve the performance of ensemble models by effectively combining the predictive power of different algorithms. Additionally, these results emphasize the importance of refining the models, especially in improving recall for fault types that are harder to detect, which could be achieved through techniques like class weighting or resampling.

Further work could also focus on expanding the dataset to include additional fault types and operational conditions, which could help improve the model's generalization ability. Incorporating advanced deep learning methods, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), could potentially offer improved performance in capturing more complex patterns within sensor data. Real-time integration of these machine learning models into automotive diagnostic systems could enable predictive maintenance, providing valuable insights for preventing costly repairs and extending vehicle lifespan.

This study highlights the potential of AI-based diagnostic systems for predictive maintenance in the automotive industry. While the results are promising, further advancements are needed to improve model performance, especially for fault types that are more difficult to detect. The development of more sophisticated ensemble methods, the expansion of training datasets, and the integration of deep learning techniques hold great promise for advancing automotive diagnostics and ensuring the reliability of modern vehicle systems.

4. CONCLUSION

This study evaluated the performance of three machine learning models RF, MLP, and an ensemble approach for automotive engine fault detection using the EngineFaultDB dataset. The ensemble model achieved an overall accuracy of 74.89%, comparable to MLP (74.96%) and RF (74.82%). The ensemble demonstrated perfect classification for Fault Types 0 and 1, indicating strong performance on these classes.

However, the model's accuracy dropped to approximately 50% for Fault Types 2 and 3, highlighting challenges in detecting more complex or underrepresented fault types. This discrepancy emphasizes the need for further model refinement, particularly in addressing subtle or rare faults. Additionally, the reliance on existing features points to the importance of advanced feature engineering to enhance performance.

To improve accuracy and robustness, future work should investigate advanced ensemble techniques such as stacking or boosting, and explore deeper model architectures. Incorporating additional data sources and diverse fault representations may further enhance detection, especially for complex fault classes. Real-time deployment of these models could enable proactive predictive maintenance, reducing repair costs and vehicle downtime.

Overall, this work underscores the promise of AI-driven diagnostic systems for predictive maintenance in the automotive industry while highlighting key areas for improvement in fault classification. Continued advancement in ensemble methods, feature engineering, and model design will be crucial to improving reliability and effectiveness in practical applications.

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