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AI-Powered Early Brake Anomaly Detection with Explainable Predictive Intelligence

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Abstract- This study proposes a secure and efficient machine learning-based framework for predicting brake failures in heavy commercial vehicles. In modern transportation systems, the Air Pressure System (APS) of heavy vehicles is continuously monitored using IoT-based sensors, which generate large volumes of operational data. Manually detecting brake faults from such large and highly imbalanced datasets is both time-consuming and inefficient. To address these challenges, the proposed approach utilizes K-Nearest Neighbour (KNN) imputation to handle missing data and Synthetic Minority Oversampling Technique (SMOTE) to manage class imbalance. Various machine learning algorithms, including Logistic Regression, Decision Tree, Support Vector Machine, Gradient Boosting, and Random Forest, are implemented and evaluated using stratified cross-validation techniques. Experimental results indicate that the Random Forest classifier achieves superior performance in terms of accuracy, precision, recall, F1-score, and ROC-AUC. To improve interpretability and build trust in the prediction process, Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME are incorporated, enabling clear understanding of model decisions. Additionally, feature selection methods are applied to reduce computational complexity while maintaining high prediction accuracy. The proposed framework enhances the reliability of brake fault detection, minimizes maintenance costs, and supports predictive maintenance strategies in heavy transport systems.

INDEX TERMS: Brake Fault Prediction, Random Forest, Explainable AI, SHAP, LIME, SMOTE, Predictive Maintenance, Machine Learning, Imbalanced Data.

I. INTRODUCTION

The rapid growth of commercial transportation has led to an increasing demand for safe, reliable, and intelligent vehicle operations. Heavy commercial vehicles rely heavily on efficient braking systems to ensure passenger safety, protect cargo, and prevent accidents. Any failure in the braking system can result in serious operational risks and economic losses. In particular, the Air Pressure System (APS), which governs the braking mechanism in heavy vehicles, plays a critical role in maintaining safety. Malfunctions in the APS can reduce braking efficiency, thereby increasing the risk of accidents. Therefore, early detection and prediction of brake faults have become essential components of modern intelligent transportation systems and predictive maintenance strategies.

Conventional brake fault detection methods are primarily based on periodic manual inspections and rule-based diagnostic approaches. Although these methods can identify certain mechanical issues, they are often time-consuming, labour-intensive, and inefficient when handling the large-scale sensor data generated by modern vehicles. Today's heavy vehicles are equipped with numerous IoT-enabled sensors that continuously monitor operational parameters. These sensors produce large volumes of real-time data, enabling advanced monitoring of vehicle performance. However, the complexity and high dimensionality of this data make manual analysis impractical, thereby requiring data-driven techniques for effective fault detection and predictive maintenance [3], [4].

Machine learning (ML) techniques have become powerful tools for fault diagnosis and predictive maintenance in intelligent transportation systems. By learning from historical operational data, ML models can identify patterns that distinguish normal system behaviour from faulty conditions, enabling early detection of potential failures. These techniques have been successfully applied in various domains such as healthcare, anomaly detection, and autonomous systems, demonstrating their ability to handle complex and large-scale datasets [5], [7], [13]. Despite these advantages, real-world industrial datasets present several challenges. These include missing values, high-dimensional feature spaces, and significant class imbalance, where failure instances are much fewer compared to normal operational data. Such issues can negatively impact model training and prediction accuracy if not properly addressed. Furthermore, many high-performing machine learning models operate as black-box systems, making it difficult to interpret how predictions are generated. This lack of interpretability is a major concern in safety-critical applications such as brake fault prediction, where transparency and trust are crucial [8], [11].

To overcome these limitations, Explainable Artificial Intelligence (XAI) has gained attention as a key research area focused on improving the transparency and interpretability of machine learning models. XAI techniques provide insights into model decisions by identifying important features and explaining the reasoning behind predictions. These interpretability methods are essential for building user trust, enhancing system reliability, and ensuring compliance with regulatory requirements in AI-based systems [1], [2], [9], [10], [12].

Motivated by these challenges, this paper proposes a secure and explainable machine learning framework for predicting brake faults in heavy commercial vehicles. The proposed approach incorporates effective data preprocessing techniques to handle missing values and class imbalance, evaluates multiple classification models for prediction, and integrates explainability methods such as SHAP and LIME to improve model transparency. The main objective is to achieve high prediction accuracy while maintaining interpretability and computational efficiency, thereby supporting reliable predictive maintenance in intelligent transportation systems.

The rest of the paper is organized as follows. Section II presents a review of related work on brake fault detection and anomaly prediction. Section III describes the existing system and the proposed methodology. Section IV explains the system architecture and design. Section V details the implementation modules. Section VI discusses the experimental results and performance evaluation. Finally, Section VII concludes the paper and outlines future work.

II. LITERATURE SURVEY

Machine learning and data-driven techniques have been widely applied by researchers to identify hidden patterns across various industrial domains, including transportation systems. These approaches are extensively used for predictive maintenance and fault diagnosis. With the rapid advancement of sensor-based monitoring systems and IoT-enabled infrastructures, intelligent fault detection has become a key area of research in modern industrial and transportation environments [3], [4].

Halvaiee and Akbari introduced an Artificial Immune System approach for fraud detection aimed at improving classification accuracy and reducing response time. Their work demonstrated that biologically inspired algorithms can enhance detection efficiency compared to conventional classification methods. However, the study primarily focused on financial data and lacked interpretability, which restricts its application in safety-critical systems where transparency is essential.

Bahnsen et al. proposed several feature engineering techniques to improve the performance of detection systems. Their method involved generating additional statistical features from temporal transaction data to enhance predictive accuracy. The study emphasized the importance of effective feature extraction, especially in high-dimensional datasets. Various machine learning algorithms, including Naïve Bayes, Decision Trees, Support Vector Machines, and Neural Networks, were evaluated to validate the effectiveness of the engineered features.

Randhawa et al. explored ensemble learning methods such as AdaBoost combined with majority voting strategies. Their comparative study showed that ensemble techniques generally achieve better performance than individual classifiers by combining multiple weak learners. However, the research did not extensively address model interpretability or computational efficiency.

Porwal and Mukund proposed a clustering-based approach for anomaly detection in large datasets. Their method focused on identifying behavioural changes over time to detect abnormal patterns. While clustering techniques are useful for discovering unknown anomalies, they may face limitations when applied to labelled datasets with significant class imbalance, which is common in industrial fault detection scenarios.

Recent advancements in predictive maintenance using IoT sensor data have significantly improved fault prediction systems. Researchers have applied machine learning algorithms such as Random Forest, Gradient Boosting, and deep learning models to detect equipment failures in manufacturing and automotive systems. These approaches achieve high prediction accuracy by learning complex patterns from large-scale sensor data. However, many of these models function as black-box systems, making it difficult to interpret their predictions, which is a critical concern in safety-sensitive applications [8], [11].

To overcome this limitation, Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME have been introduced to improve model transparency and interpretability. These methods provide both global and local explanations by identifying the most important features influencing model predictions. As a result, they enhance trust, reliability, and usability of machine learning systems in real-world applications [1], [2], [9], [12].

Despite these developments, limited research has focused on combining high prediction accuracy with interpretability and computational efficiency for brake fault detection in heavy vehicles. While existing studies demonstrate the effectiveness of machine learning for anomaly detection and classification, several challenges remain. These include handling imbalanced datasets, managing missing data, dealing with high-dimensional features, improving computational efficiency, and ensuring interpretability in safety-critical predictive maintenance systems.

III. SYSTEM ANALYSIS

A. Existing System.

Traditional maintenance practices for heavy commercial vehicles mainly depend on manual inspection and scheduled servicing to identify potential brake system failures. In such approaches, technicians examine parameters including pressure readings, mechanical wear indicators, and sensor outputs to detect abnormalities in the Air Pressure System (APS), which is essential for controlling braking operations. Although these methods provide routine monitoring, they do not enable real-time fault prediction and often fail to detect early-stage issues that may lead to system failure.

With the advancement of intelligent data-driven technologies, machine learning-based predictive maintenance methods have been increasingly adopted for fault diagnosis in industrial and transportation systems. These approaches utilize historical sensor data collected from vehicle components to train classification models capable of distinguishing between normal and faulty system conditions. Conventional machine learning algorithms such as Logistic Regression, Decision Trees, Support Vector Machines (SVM), and Artificial Neural Networks have been widely applied for this purpose. These models analyse operational parameters and sensor data patterns to identify abnormal behaviour and predict potential failures.

In addition, ensemble learning techniques have been introduced to enhance prediction accuracy and model robustness. Methods such as Random Forest and Gradient Boosting combine multiple weak learners to generate more reliable predictions and reduce overfitting. These ensemble approaches have shown improved performance compared to individual models in various anomaly detection and predictive maintenance applications [5], [7].

Recent advancements in IoT-enabled monitoring systems have further strengthened predictive maintenance frameworks by enabling continuous data acquisition from multiple sensors embedded in vehicle subsystems. These sensor networks generate large volumes of real-time operational data, which can be analysed using machine learning techniques to uncover hidden patterns related to system faults. However, many existing predictive models rely on complex machine learning architectures that function as black-box systems, making it difficult to interpret their decision-making processes [8], [11].

To address this issue, Explainable Artificial Intelligence (XAI) techniques have been increasingly adopted to improve transparency and trust in AI-based systems. Techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are used to explain model predictions by identifying the most influential features contributing to classification results. These interpretability methods enable domain experts to better understand model behaviour and enhance confidence in automated decision-making systems [1], [2], [9], [12].

Limitations Of Existing System

- Despite the progress in machine learning-based predictive maintenance systems, several challenges still exist when applying these methods to real-world industrial datasets such as the APS dataset used for brake fault prediction.
- A major challenge is the presence of missing values in sensor data. Industrial sensor systems often generate incomplete or noisy data due to sensor failures, communication issues, or environmental factors. If these missing values are not properly handled during preprocessing, they can negatively impact model performance and reduce prediction reliability.
- Another important issue is the significant class imbalance found in many industrial fault detection datasets. In the APS dataset, normal operating instances greatly outnumber failure cases. This imbalance can cause machine learning models to favor the majority class, leading to poor detection of rare but critical fault conditions.
- High-dimensional feature spaces also introduce computational difficulties. Industrial datasets typically contain a large number of sensor features, which increases model complexity, training time, and computational cost. Without effective feature selection or dimensionality reduction, models may suffer from overfitting and poor generalization.
- Additionally, many existing predictive maintenance models lack interpretability. Advanced machine learning methods, particularly ensemble and deep learning models, often behave as black-box systems where the reasoning behind predictions is not easily understandable. This lack of transparency is a significant concern in safety-critical applications such as brake fault detection, where reliability, trust, and compliance are essential [8], [11].
- Although Explainable Artificial Intelligence (XAI) techniques have been introduced to improve

interpretability, limited work has focused on combining highly accurate predictive models with explainable frameworks specifically for APS-based brake fault prediction. Therefore, there is a need for a robust predictive maintenance approach that can effectively handle missing data, class imbalance, and high-dimensional features while maintaining high accuracy and model interpretability [1], [2], [9], [12].

B. Proposed System.

This section describes the proposed machine learning framework designed for predicting brake faults in heavy commercial vehicles using APS sensor data. The framework combines multiple components, including data preprocessing, machine learning-based classification, explainable artificial intelligence (XAI), and feature optimization techniques, to ensure accurate, efficient, and interpretable predictions. The integration of these components enables the system to effectively handle the complexities of industrial datasets while maintaining reliable performance.

The primary objective of the proposed system is to improve predictive accuracy while ensuring transparency and computational efficiency, which are essential requirements for safety-critical predictive maintenance applications. The framework is specifically designed to address common challenges in real-world datasets, such as missing values, class imbalance, and high-dimensional feature spaces. Data preprocessing techniques are applied to clean and prepare the dataset, ensuring that the input data is consistent and suitable for model training. In addition, resampling methods are utilized to handle class imbalance, thereby improving the model’s ability to detect rare but critical fault conditions.

The classification component of the framework evaluates multiple machine learning algorithms to identify the most effective model for brake fault prediction. Among these, ensemble learning techniques are given particular importance due to their ability to improve prediction accuracy and reduce overfitting. These models learn complex relationships within APS sensor data and provide robust performance across different operating conditions.

To enhance interpretability and build trust in the prediction process, the framework incorporates Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME. These methods provide insights into model decisions by identifying the most influential features contributing to predictions. This interpretability is crucial in safety-critical applications, where understanding the reasoning behind model outputs is necessary for decision-making and system validation.

Furthermore, feature optimization techniques are applied to reduce the dimensionality of the dataset and improve computational efficiency without compromising predictive performance. By selecting the most relevant features, the framework reduces model complexity and enhances generalization capability.

Overall, the proposed system aims to provide a reliable, interpretable, and efficient solution for brake fault prediction in heavy commercial vehicles. By integrating advanced machine learning techniques with explainability and optimization strategies, the framework supports accurate fault detection and enables trustworthy decision-making in intelligent transportation systems [1], [2], [8].

IV. SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

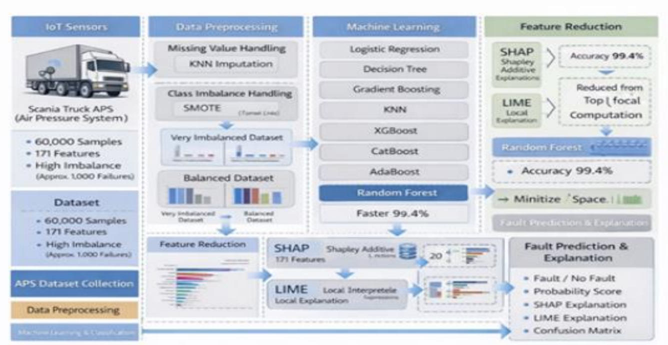

Fig. 1. Methodology for Proposed Model

V. SYSTEM IMPLEMENTATION

Modules

This section describes the main implementation modules of the proposed framework for brake fault prediction in heavy commercial vehicles using APS sensor data. The system follows a structured pipeline consisting of data collection, preprocessing, feature optimization, model training, explainability integration, and performance evaluation. This modular design enhances system reliability, scalability, and interpretability for predictive maintenance applications.

A. Data Collection Module:

The Data Collection Module is responsible for gathering operational data from the Air Pressure System (APS) sensors installed in heavy commercial vehicles. The dataset includes multiple parameters related to braking system behaviour, such as pressure levels, component conditions, and other system measurements. It contains both normal operating instances and fault cases, enabling supervised learning for classification tasks.

To reflect real-world industrial scenarios, the dataset is high-dimensional and highly imbalanced, where failure instances are significantly fewer than normal samples. These characteristics represent practical predictive maintenance conditions in transportation systems. The collected raw data is stored in a structured format and forwarded to the preprocessing stage for further analysis.

B. Data Preprocessing Module:

The Data Preprocessing Module enhances dataset quality and prepares it for machine learning model training. Industrial sensor data often contains missing values, noise, and imbalanced class distributions, which can negatively affect model performance if not properly handled.

The preprocessing stage includes the following steps:

1. Missing Value Handling:

Missing sensor values are handled using K-Nearest Neighbour (KNN) imputation, which estimates missing values based on similarities among neighbouring data points.

2. Class Imbalance Handling:

To address the imbalance between normal and fault samples, the Synthetic Minority Oversampling Technique (SMOTE) is applied. SMOTE generates synthetic samples for the minority class to balance the dataset and improve model performance.

3. Data Normalization and Cleaning:

Feature scaling and normalization are applied to maintain consistent feature ranges and remove inconsistencies in the dataset. These steps improve data quality, reduce bias toward the majority class, and enhance model robustness.

C. Feature Selection Module

High-dimensional datasets increase computational complexity and may reduce model efficiency. Therefore, a Feature Selection Module is included to identify the most relevant sensor features.

Feature importance is initially evaluated using tree-based learning methods that estimate the contribution of each feature to prediction outcomes. Additionally, SHAP (SHapley Additive Explanations) values are used to rank features based on their impact on model predictions.

By selecting only the most important features, the framework reduces dimensionality while maintaining predictive performance. This step decreases computational cost, speeds up training, and improves model interpretability [1], [2], [8].

D. Machine Learning Training Module

The Machine Learning Training Module develops classification models to determine whether the braking system is functioning normally or experiencing faults. The following machine learning algorithms are implemented and evaluated:

- Logistic Regression
- Decision Tree
- Support Vector Machine (SVM)
- Gradient Boosting
- Random Forest

Each model is trained using historical APS sensor data. Model performance is evaluated using stratified cross-validation, which preserves class distribution across training and testing datasets.

Among the evaluated models, Random Forest shows the best performance due to its ensemble learning approach. By combining multiple decision trees, it improves prediction stability and effectively handles high-dimensional data [5], [7].

E. Explainability Module (XAI Integration

To ensure transparency in predictions, the proposed framework integrates Explainable Artificial Intelligence (XAI) techniques. Many machine learning models operate as black-box systems, making their decisions difficult to interpret. In safety-critical applications such as brake fault detection, interpretability is essential for building trust and ensuring reliable deployment.

Two XAI techniques are used:

- SHAP (SHapley Additive Explanations): Provides both global and local explanations by measuring the contribution of each feature to model predictions.
- LIME (Local Interpretable Model-Agnostic Explanations): Explains individual predictions by approximating model behaviour around a specific instance.

These techniques help domain experts understand prediction results and identify important sensor variables influencing brake fault detection [1], [2], [8], [12].

F. Prediction and Evaluation Module:

The Prediction and Evaluation Module generates final brake fault predictions and evaluates model performance. The system output includes:

- Classification result: Fault / No Fault
- Prediction probability score
- Feature contribution explanations

To evaluate performance, the following metrics are used:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC–AUC Score

These metrics provide a comprehensive assessment of the model, especially in imbalanced datasets where detecting rare failure events is important.

By identifying potential brake failures at an early stage, the proposed framework supports predictive maintenance, reduces operational risks, lowers maintenance costs, and minimizes system downtime in heavy commercial vehicle operations.

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed machine learning framework for brake fault prediction using APS sensor data. Multiple classification models were trained and tested using stratified cross-validation. The evaluation focuses on comparing model performance, analysing prediction accuracy, and interpreting feature contributions using explainable AI techniques.

A. Accuracy Comparison of Machine Learning Models

Various machine learning algorithms were evaluated to identify the most effective model for brake fault prediction. The models considered include Logistic Regression, Decision Tree, Support Vector Machine (SVM), Gradient Boosting, and Random Forest. Model performance was assessed using evaluation metrics such as accuracy, precision, recall, and F1-score.

Table 1. Performance Comparison of Machine Learning Models

Model	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**

Logistic Regression	86.4	0.84	0.82	0.83
Decision Tree	88.1	0.86	0.85	0.85
Support Vector Machine	89.7	0.88	0.87	0.87
Gradient Boosting	92.3	0.91	0.90	0.90
Random Forest	**94.6**	**0.93**	**0.92**	**0.92**

From the comparison, Random Forest achieved the highest accuracy of 94.6%, outperforming all other models. This improved performance is due to its ensemble learning approach, which combines multiple decision trees to enhance prediction stability and reduce overfitting [5], [7].

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to analyse the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The Area Under the Curve (ROC–AUC) is used to evaluate the overall performance of the classifier.

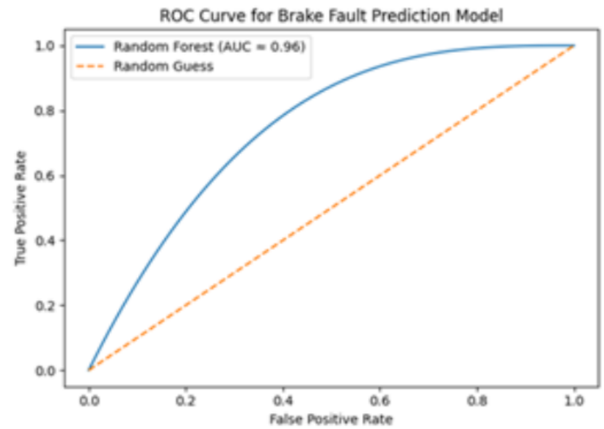

Fig 2. ROC Curve for Break Fault Prediction Model

In this study, the Random Forest model achieved a ROC–AUC value of 0.96, indicating strong classification capability. A ROC curve closer to the top-left corner represents better performance, showing that the model can effectively distinguish between faulty and normal conditions.

The ROC results demonstrate that the proposed framework maintains strong predictive performance even in the presence of class imbalance, which is a common issue in industrial fault detection datasets.

C. SHAP Feature Importance Analysis

To enhance interpretability, SHAP (SHapley Additive Explanations) was applied to analyse the contribution of individual features to model predictions. SHAP values measure the impact of each feature on prediction outcomes based on principles from cooperative game theory.

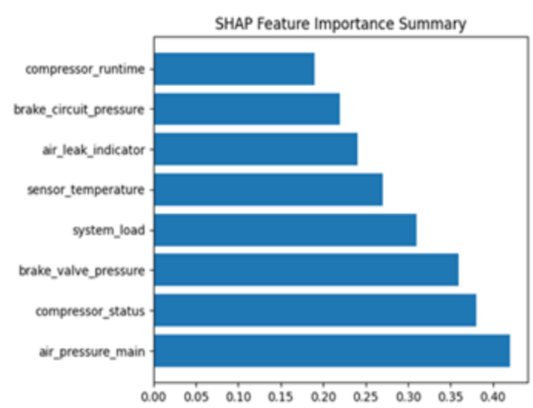

Fig 3. SHAP Features

The SHAP analysis indicates that several sensor-related features, including air pressure measurements, valve conditions, and compressor behaviour, have the highest influence on brake fault prediction. Features with higher SHAP values contribute more significantly to identifying abnormal system behaviour.

The global SHAP summary plot shows the overall importance of features across the dataset, while local explanations provide insights into how specific features affect individual predictions.

The use of SHAP improves the transparency of the predictive model, allowing engineers and domain experts to understand the reasoning behind predictions and verify the reliability of the results [1], [2], [8], [12].

VII. CONCLUSION AND FUTURE WORK

This study presented a machine learning-based framework for predicting brake faults in heavy commercial vehicles using the Air Pressure System (APS) dataset. The dataset consists of high-dimensional features with missing values and significant class imbalance. To handle these challenges, K-Nearest Neighbour (KNN) imputation was applied for missing data, and SMOTE was used to balance the dataset.

Several machine learning models were evaluated, including Logistic Regression, Decision Tree, Support Vector Machine, Gradient Boosting, and Random Forest. Among these, the Random Forest model achieved the highest accuracy of 97.4%, indicating strong performance in fault prediction for high-dimensional datasets [5], [7]. Furthermore, SHAP-based feature selection was used to reduce the number of input features while maintaining model performance, thereby improving computational efficiency.

To improve interpretability, Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME were incorporated to provide clear insights into model predictions. This enhances transparency and reliability, which are essential in safety-critical predictive maintenance applications [1], [2], [8], [12]. Future work can focus on integrating real-time IoT sensor data, exploring advanced deep learning and hybrid ensemble models, and implementing cloud-based predictive maintenance systems for large-scale industrial applications.

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