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Performance Analysis of ML Algorithms for Brake System Failure Detection

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ABSTRACT

Hydraulic brakes play a pivotal role in ensuring passengers, drivers and goods safety in vehicles making them indispensable components. Therefore, monitoring and predicting failure of brake becomes very important. Machine learning (ML) based algorithms are used for predicting the failure of the braking system. In this paper, we have carried out performance analysis of almost all major algorithms (ML classifiers) to predict and monitor the brake failure. We used dataset from Scania Trucks in these algorithms and their performances are evaluated using the parameters, sensitivity, specificity and accuracy. Almost all algorithms give accuracy around 98%, except Naïve Bayes having 92% accuracy. It has been found that the stochastic gradient descent (SGD) algorithm yields better performance across all parameters: sensitivity 97.709%, specificity 96.146%, and accuracy 96.925%.

KEYWORDS

Air pressure system (APS), Feature selection, Brake failure monitoring, PCA, Gradient Boosting Classifier, Support Vector Machine (SVM), Decision Tree, Random Forest, KNN Classifier.

1. INTRODUCTION

The brake system in automobile is a critical component responsible for ensuring vehicle safety, their control and most importantly passenger and driver's safety [1]. Typically, it consists of hydraulic, mechanical, or electronic elements that help to slow down or stop a vehicle. In contemporary vehicles, hydraulic brake systems, commonly employed, initiate hydraulic pressure generation upon depressing the brake pedal, activating a master cylinder. The force is subsequently conveyed via brake lines to brake calipers or wheel cylinders, resulting in the activation of brake pads or shoes against brake drums and discs. The friction produced among these elements transforms kinetic energy into heat, effectively slowing down the vehicle. In addition to hydraulic systems, some vehicles employ mechanical or electronic braking technologies. Each of them comes with its own advantages and applications. However, failure to effectively get brake applied is a big concern. This brake failure causes significant loss of materials and human. Different braking systems have different accuracy, effectiveness and time of execution. Hence, it becomes very important to monitor or predict such failure [2].

In hydraulic brake systems, failures can stem from issues such as fluid leaks, worn-out components, or malfunctioning valves. Routine inspections and preventive maintenance play a crucial role in identifying potential failures before they compromise braking performance [3]. Moreover, progress in technology has resulted in the incorporation of electronic systems like anti-lock braking systems (ABS) and brake wear sensors, improving the ability to identify abnormalities. ABS, for instance, monitors wheelspeed and adjusts brake pressure to prevent skidding. Brake wear sensors provide timely alerts when brake pad thickness approaches critical levels. The combination of regular inspections and technological innovations in detection mechanisms contributes to overall reliability and safety of hydraulic brake systems in modern vehicles [4].

In the realm of failure detection in brake systems, existing work has explored various approaches, both with and without the integration of machine learning. Traditional methods without machine learning often involve sensor-based monitoring and diagnostic techniques. These approaches rely on sensors to detect changes in brake system parameters, such as fluid pressure, temperature, and wheel speed, to identify potential issues. On the other hand, machine learning has been increasingly employed to enhance the accuracy and efficiency of failure detection [5]. Researchers have utilized machine learning algorithms to analyse complex datasets generated by sensors, identifying patterns indicative of potential brake system failures. This allows for more nuanced and predictive analysis, enabling proactive maintenance and reducing the risk of unexpected malfunctions. While non-machine learning methods provide effective monitoring, machine learning techniques offer a promising avenue for more sophisticated and adaptive brake system failure detection in the ever-evolving landscape of automotive safety [6].

This paper aims at classification of highly imbalanced and overlapping data classes in an effective manner. We have made use of dataset from University of California Irvine machine learning repository (UCI). The dataset comprises information gathered from routine operations of large Scania trucks. The focus of investigation centers on the air pressure system that is responsible for producing compressed air utilized in diverse truck functions, including braking and gear shifting.

The positive class within the dataset signifies instances of component failures specifically related to the air pressure system (APS), while the negative class encompasses instances of truck failures attributed to components unrelated to the APS. We used various algorithms like Gradient Support, vector machine, decision Tree, Random forest, KNN classifier, Boosting classifier, Voting classifier, MLP classifier, Naïve Bayes, SGD classifier, and AdaBoost classifier [4]. By employing these algorithms we were able to identify the best among them, achieving a sensitivity of 98.596%.

The content of rest of the paper is organized as follow. Section II clarifies about the architecture of the system. Section-III presents the algorithms in braking system. Section IV highlights the simulated results. Finally, Section V concludes the paper.

2. MOST RECENT AND RELEVANT WORK

Few studies have been carried out for monitoring, predicting brake application in different kind of vehicles for different types of brakes. Prasoon et al. [7] assessed machine learning algorithms to predict air pressure system failures in Scania trucks. The hybrid model proved most efficient offering high accuracy, sensitivity, specificity, and cost-effectiveness. Despite logistic regression's surpass performance, Random forest and XGBoost models excelled. The results have meaningful implications for enhancing truck maintenance, reducing costs, improving safety, and extending applications to predict failures in other automotive components.

Radhika Raveendran et al. [8] applied random forest and decision tree models to detect faults in the air brake system. The random forest approach exhibited superior predictive accuracy, achieving 94.47%. Conducted on a hardware-in-loop (HiL) test bench, experiments generated datasets utilized in both the testing and training phases of the diagnostic algorithm. The suggested diagnostic approach is suitable for monitoring the health of air brakes and has the potential to be expanded for the creation of a fault-tolerant brake control system for heavy commercial road vehicles (HCRVs). This could enhance overall vehicle performance in situations where faults are present. Jegadeeshwaran et al. [9] explored vibration-based faults diagnosis in automotive hydraulic brake systems through the application of the clonal selection classification (CSC) algorithm. Simulating nine fault conditions, vibration signals were captured and analyzed with twelve statistical features. Feature selection and classification with the clonal selection classification algorithm resulted in a 96% correct classification rate out of 550 datasets, showcasing the algorithm's effectiveness.

Likewise, researchers in [10] investigated the efficiency of the nested dichotomy (ND) algorithm as a meta-learning approach for diagnosing brake faults in automotive hydraulic systems. By simulating nine fault scenarios and employing statistical features extracted from vibration signals, the study utilized ensemble algorithms such as ND, class balanced nested dichotomy (CBND), and data near balanced nested dichotomy (DNBND) with random forest trees as the underlying algorithm.

Notably, the CBND model exhibited 1.09% misclassification rate for three fault conditions, positioning. It as a promising candidate for practical applications in hydraulic brake system fault diagnosis. Authors in. [1] confirmed the feasibility of hydraulic brake system fault diagnosis using vibration signals and machine learning techniques, especially for common faults. Simulated faults tested in a lab under static conditions yielded accurate classification with the C4.5 decision tree and SVM classifier algorithms. For acceptable misclassification, the top five statistical features suffice, but for enhanced accuracy, seven features are recommended. The radial basis function (RBF) kernel, particularly in the support vector machine (C-SVM) model, where ***c*** is a regularization parameter showed superior classification accuracy among SVM kernel functions. Authors in [11] used artificial intelligence for brake fault diagnosis based on vibration signals. Simulating seven fault conditions on a hydraulic brake setup, twelve selected features and algorithms (Naïve Bayes Updateable, Logit Boost Meta, Hoeffding Tree, Random Committee) were employed. Among 74 samples, Logit Boost Meta achieved 88.22% correct classification rate, making it the preferred algorithm. The study suggests potential for a graphical user interface (GUI) to inform drivers of brake conditions for accident prevention.

3. SYSTEM MODEL AND ARCHITECTURE

In Figure 1, the system architecture delineates a meticulous process to monitor and analyze the brake system's health comprehensively. The piezoelectric accelerometer [12], strategically placed near the brake components serves as the primary transducer for capturing vibrations. This choice is underpinned by the accelerometer's ruggedness, wide frequency response and its capacity to discern subtle vibrations amidst larger forces, making it an ideal instrument for machine condition monitoring. The heart of the system lies in the subsequent data processing and feature extraction performed on the stored vibration signals [13]. Leveraging the advanced capabilities of the data acquisition (DAQ) system, the analysis focuses on identifying distinctive features that serve as reliable indicators of the brake system's condition. These features could range from frequency patterns to amplitude variations, providing insights into potential faults [14]. This systematic approach empowers the system not only to detect anomalies but also to

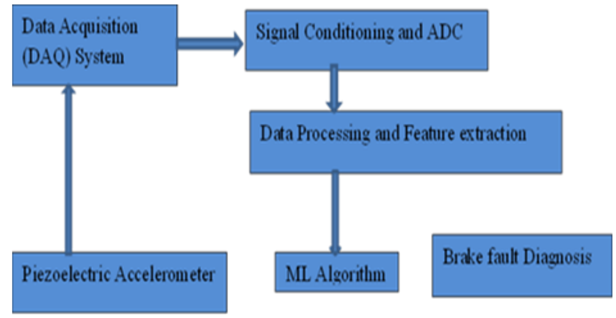


Fig. 1 System Architecture.

predict and prevent issues, thereby enhancing the overall reliability and safety of the brake system in the monitored vehicle.

4. ALGORITHM DESIGN AND DESCRIPTION

The system work flow is given in Figure 2. Brake fault diagnosis utilizing a machine learning model involves the systematic analysis of sensor data from the braking systemto identify potential anomalies or faults. Initially, relevant features are extracted from the sensor data, encompassing parameters such as temperature, pressure, and vibration. These features serve as inputs to a trained machine learning model which has learned patterns indicative of normal and faulty brake behavior during its training phase. The model, often employing algorithms such as decision trees, neural networks, or, support vector machines evaluates the input features in real-time to discern deviations from the expected behavior. Upon detecting a fault or anomaly, the system generates alerts, allowing for timely intervention and proactive maintenance. Continuous learning capability of the machine learning model further enhances its fault detection accuracy over time, contributing to improved brake system reliability and safety. In our implementation, the machine learning model's effectiveness in fault detection was validated using a dataset obtained from Scania trucks, focusing on the APS.

i. Dataset

The data in the dataset was obtained from Scania trucks.The main focus of the system is the air pressure system. It produces air that is pressurized which in turn is required for the smooth functioning of the truck. The signal from the accelerometer undergoes a sophisticated transformation within the data acquisition system. The NI USB-4432 model, equipped with five analog input channels and an impressive sampling rate of 102.4 kilo samples per second at 24-bit resolution ensures accurate capture of intricate vibration patterns. The signal conditioning unit, featuring an analog-to-digital converter (ADC) and a charge amplifier further refines and digitizes the vibrations. This digitized information is then transmitted to the computer through a USB port for storage in secondary memory.

In the experiments, the training set handles 60k samples, in which 59k is of the negative class and the rest positive class. 16k samples are considered for test set. The data set consist of response time of the brake, distance before stopping, distribution of the brake force, feel of the brake pedal, the noise that is produced when a brake(s) is applied. Additionally, data set has an attribute to check the life time of a brake, the temperature, force on the brake pedal when applied, friction created betweendisc and brake pad (to bring a vehicle in stopping position the amount of applied force), the time taken between the brake applied and the vehicle stops, the distributed braking force between thefront and rear wheels, during different driving conditions the consistency of the performance of the brake during the multiple applications of brake.

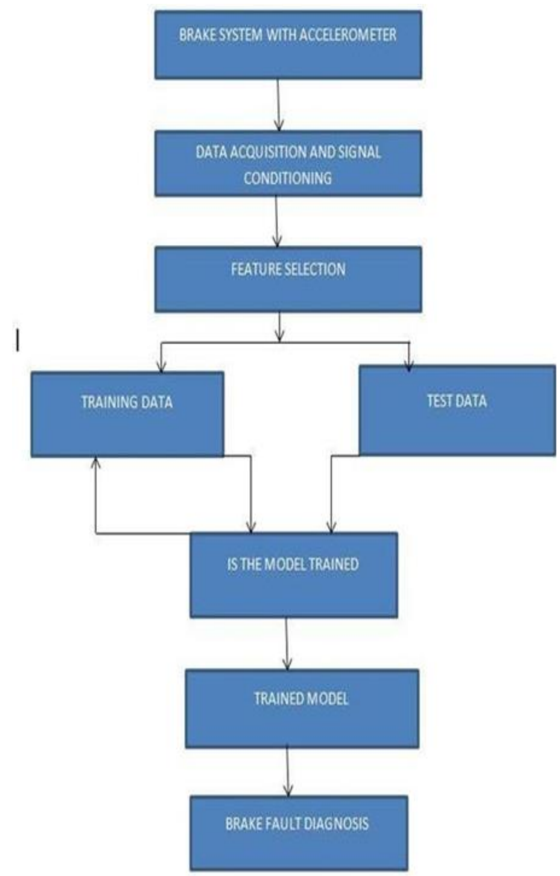


Fig. 2 Flow Diagram

The flowchart outlines a comprehensive process for diagnosing brake faults using machine learning models, starting from data collection to fault diagnosis. The initial step involves a brake system equipped with an accelerometer to capture acceleration data during braking events. This raw data undergoes data acquisition and signal conditioning, which involves filtering and converting the signals to improve their quality and ensure they are in a suitable format for analysis. Following this, feature selection is performed to identify and extract the most relevant features from the conditioned data that can effectively distinguish between normal and faulty brake conditions. These features are crucial for enhancing the performance and accuracy of the machine learning models.

The process then splits the data into two subsets: training data and test data. The training data is used to train the machine learning model, while the test data is used to evaluate the model's performance. A decision point checks whether the model has been sufficiently trained; if not, the model continues to iterate over the training data until the desired performance metrics are achieved. Once the model is adequately trained, it is deployed as the final trained model. This model is then used for real-time brake fault diagnosis, analyzing new incoming data from the brake system to accurately detect any faults. This systematic approach ensures the reliability and effectiveness of the brake fault detection system, providing critical insights to enhance vehicle safety and performance.

ii. Algorithms

Dimensionality reduction: Principal component analysis (PCA) [10] is one of the most used techniques for understanding datasets. Normally, from a set of large data set having more and redundant attributes can be reduced to the most relevant and important attributes. However, it is ensured that important information is not lost. PCA can also be used in multiple dimensional data for visualization.

Dataset Balancing: Synthetic minority oversampling technique (SMOTE) is used to solve the problem of imbalance data by using oversampling methods [15]. This is done by randomly raising the number of minority class to balance the distribution of the class. A virtual training set is generated through linear interpolation in the class which is minority. Once the oversampling is done, it is used in different classification data to process the data.

Classifiers: Different classifiers are used for the prediction of brake failure. The algorithms used are KNN, SVM, random forest, SGD, gradient descent, Voting classifier, AdaBoost, MLP, decision tree and Naive Bayes.

5. RESULTS AND DISCUSSIONS

The data collected from the Scania trucks is having 76k samples, of which the 60k samples are used for training and remaining 16k samples are used for testing. For this experiment performed, we have used many classification algorithms. In the training dataset, we have 59000 negative cases and 1000 positive cases.

Principal component analysis [10] was employed as a crucial step to manage the substantial size of our dataset effectively. In Figure 3, principal component analysis is depicted as a technique for reducing dimensionality. Given its extensive nature, comprising 171 attributes, PCA was instrumental in reducing the dimensionality of the data. Through this analysis, we condensed the dataset to a more manageable size of 10 principal components, focusing on the most relevant information. PCA serves not only to mitigate computational challenges posed by large datasets but also to emphasize the most significant features, retaining the essential patterns while streamlining the dataset for subsequent analyses. This reduction in dimensionality not only facilitates more efficient data handling but also aids in uncovering the intrinsic structures and relationships within the data, thereby enhancing the interpretability of the results.

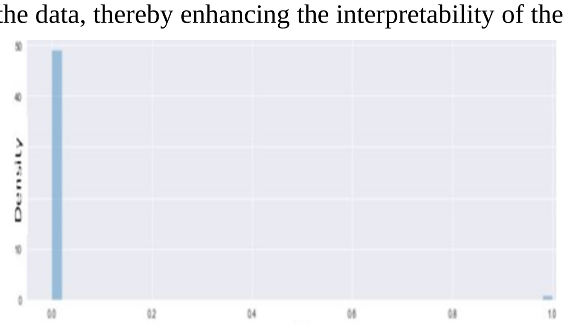
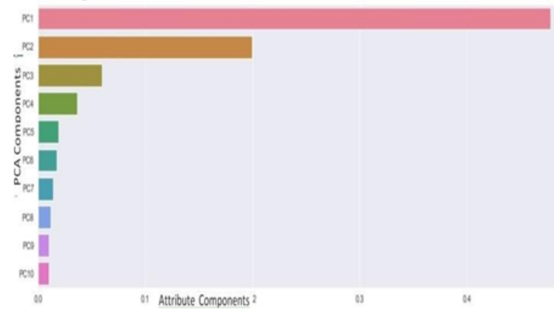


Fig. 3 PCA Analysis

As the data is highly imbalanced, we have used synthetic minority over-sampling technique algorithm [12] and plotted the correlation matrix of the same data in Figure 4 and 5. Within the realm of machine learning, SMOTE stands as a crucial technique aimed at mitigating class imbalance by creating synthetic instances for the minority class. In situations where there is a substantial imbalance between

Fig. 4 Before SMOTE implementation



classes, conventional models might demonstrate biases favoring the majority class, resulting in less-than-optimal

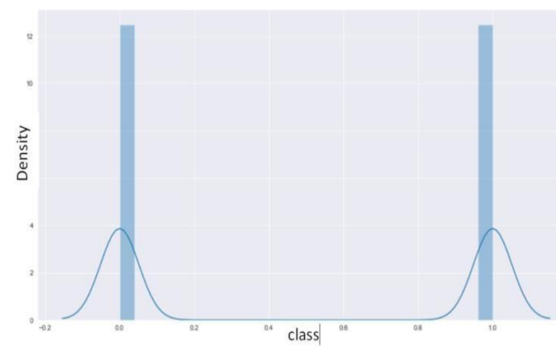


Fig. 5 After SMOTE implementation

predictive accuracy. To alleviate this problem, SMOTE addresses it by generating synthetic samples along the line segments that connect existing instances of the minority class. By introducing these artificial instances, SMOTE rebalances the class distribution, enhancing the model's ability to recognize and generalize

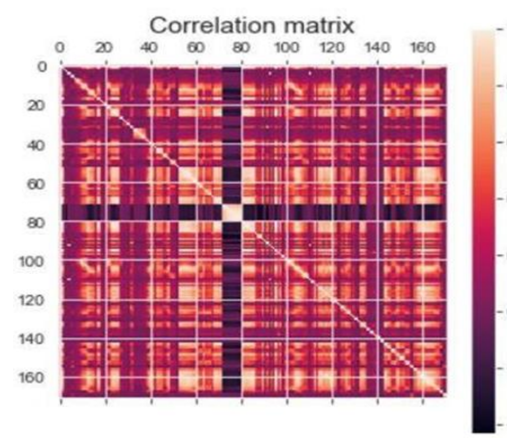


Fig. 6 Correlation Matrix

patterns within the minority class. This technique proves particularly valuable in classification tasks, contributing to more robust and unbiased machine learning models.

In Figure 6, a correlation matrix is plotted. It serves as a statistical instrument designed to measure the magnitude and direction of linear associations among variables. In the matrix, each element represents the correlation coefficient, indicating the relationship between two variables. The values range from -1, indicating a full negative correlation, to 1, indicating a complete positive correlation. A value of 0 signifies the absence of any correlation between the variables.

Table.1 A comparative study of various algorithms

Classifier Used	FN value-Test data	Sensitivity/ Recall	Specificity	Accuracy
Decision Tree	220	98.596	52.88	97.943
MLP Classifier	250	98.419	32.795	98.837
Random forest	284	98.209	35.915	99.1125
Gradient Boosting Classifier	280	98.113	70.948	97.26
Voting Classifier	297	98.103	54.913	98.893
KNN Classifier	320	97.943	87.414	97.268
AdaBoost	321	97.951	83.58	97.94
SVM	351	97.749	94.029	97.487
SGD Classifier	353	97.709	96.146	96.925
Naïve Bayes	361	97.55	98.88	92.16

Table.1 provides a comparative study of various algorithms for fault diagnosis in the context of automobile brake systems, highlighting their optimal accuracy rates. Previous works, referenced by [5]-[9] employed diverse algorithms such as Hybrid algorithm, Random forest, Clonal selection classification algorithm, Nested dichotomy algorithm, Support vector machine algorithm, and Logit boost meta algorithm. The corresponding accuracies for these algorithms range from 88.22% to 98.91%. Notably, our work stands out with the implementation of the Random forest algorithm, achieving an impressive accuracy rate of 99.11%. This table serves as a concise reference to assess the performance of different algorithms in the domain of brake fault diagnosis, showcasing the notable advancements achieved in our work with Random forest as the optimal accuracy-giving algorithm. Other performance parameters are not compared because they were not considered in the previous papers.

Table.2, presents the performance metrics of various machine learning classifiers for brake failure detection task. The classifier including decision tree, MLP classifier, random forest, gradient boosting classifier, voting classifier, KNN classifier, AdaBoost, SVM, SGD classifier, and Naïve Bayes [16-17].

For instance, the decision tree classifier demonstrates a high sensitivity of 98.596%, indicating its proficiency in correctly identifying positive instances, while its specificity is 52.88%, suggesting a relatively lower ability to discern negative instances. Random forest exhibits an impressive accuracy of 99.1125% and a high sensitivity of 98.209%, but its specificity is low as 35.915%. On the other hand, Naïve Bayes displays high specificity at 98.88% and sensitivity at 97.55%. These evaluation metrics provide an overall view of the capabilities and limitations of each classifier, assisting in the identification of a suitable model tailored to the distinct needs and preferences of the given classification assignment [18]. It is noteworthy that the performance trade-offs between sensitivity, specificity, and accuracy may influence the choice of the most suitable classifier for the given application [19-20].

Each classifier exhibits unique strengths and weaknesses in terms of sensitivity, specificity, and accuracy, which are critical metrics for evaluating their effectiveness. For example, the Decision Tree classifier shows a high sensitivity of 98.596%, highlighting its proficiency in identifying actual brake failure cases. However, its specificity is relatively low at 52.88%, indicating a higher likelihood of false positives where non-failure cases are incorrectly flagged as failures. On the other hand, the Random Forest classifier demonstrates the highest accuracy at 99.1125% and a strong sensitivity of 98.209%, but it struggles with a specificity of 35.915%, suggesting it might generate more false alarms. Naïve Bayes, while having the lowest accuracy at 92.16%, excels in specificity at 98.88%, making it highly reliable in correctly identifying non-failure instances, albeit at the cost of missing some actual failures.

Table.2 Analysis of classifiers using different parameters

Ref. No.	Algorithm	Accuracy
[5]	Hybrid	98.60
[6]	Random forest	94.47
[7]	Clonal selectionclassification	96.00
[8]	Nested dichotomy	98.91
[1]	Support vector machine	98.72
[9]	Logit boost meta	88.22
Our work	Random Forest	99.11

The varying performance metrics of these classifiers underscore the trade-offs inherent in model selection for brake failure detection【18-20】. High sensitivity models, such as the Gradient Boosting Classifier with a sensitivity of 98.113% and specificity of 70.948%, are crucial in applications where detecting every possible failure is paramount, even if this means accepting a higher rate of false positives. Conversely, models like SVM and SGD, which offer high specificity (94.029% and 96.146%, respectively), are advantageous in scenarios where minimizing false alarms is essential, despite their slightly lower sensitivities. The KNN Classifier, with its high specificity of 87.414% and a decent sensitivity of 97.943%, provides a balanced approach. Therefore, the choice of the most suitable classifier must consider the specific priorities of the brake failure detection task, such as whether the emphasis is on capturing all potential failures or on reducing false positives. These trade-offs between sensitivity, specificity, and accuracy are pivotal in tailoring the model to meet the distinct needs of the application, ensuring optimal performance and reliability in real-world scenarios.

6. CONCLUSION

Performance analysis of various ML algorithms is carried out for predicting and monitoring braking systems, especially, hydraulic brake system. Algorithms like KNN, SVM, random forest, SGD, gradient descent, voting classifier, AdaBoost, MLP, decision tree and Naive Bayes have been used. It is found that although, most of them offer very high accuracy of around 98% except Naïve Bayes (92%), but SGD offers better performance for all 3- major performance parameters. We have only utilized a dataset generated from Scania trucks, which are heavy vehicles. They might not apply for light vehicles and bikes. To conclude the prediction and monitoring, dataset from all kinds of all vehicles might be required.

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