Brake Health Prediction Using LogitBoost Classifier Through Vibration Signals - A Machine Learning Framework

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ABSTRACT

Brake is one of the crucial elements in automobiles. If there is any malfunction in the brake system, it will adversely affect the entire system. This leads to tribulation on vehicle and passenger safety. Therefore, the brake system has a major role to do in automobiles and hence it is necessary to monitor its functioning. In recent trends, vibration-based condition monitoring techniques are preferred for most condition monitoring systems. In the present study, the performance of various fault diagnosis models is tested for observing brake health. A real vehicle brake system was used for the experiments. A piezoelectric accelerometer is used to obtain the signals of vibration under various faulty cases of the brake system as well as good condition. Statistical parameters were extracted from the vibration signals and the suitable features are identified using the effect of the study of the combined features. Various versions of machine learning models are used for the feature classification study. The classification accuracy of such algorithms has been reported and discussed.

1. INTRODUCTION

Brake fault diagnosis is one of the preventive maintenance approaches for avoiding major damage. Early detection of the defects can prevent the system breakdown or severe damage. Hence, a decision support tool such as a condition monitoring system will help to recognize the failures. The failure or malfunction of the brake system is identified using some warning signs or symptoms. Vibration signals can however be modified by brake faults such as reservoir leak, mechanical fade of drum brake, wearing of brake pads, etc. (Alamelu Mangahi & Jegadeeshwaran 2019). Hence, condition monitoring of a brake system through vibration signals is studied in the paper. The brake components produce non-stationary vibration signals. Hence, it is necessary to preprocess the vibration signals for identifying the faults. Feature-based study is one of the powerful approaches that can be solved using machine learning-driven data models (Yin, Ding, Haghani, Hao & Zhang 2021; Manghai & Jegadeeshwaran 2017). The implementation of machine learning occurs in the following steps: feature extraction, feature selection, and feature classification.

The raw vibration signals are segregated as features. Numerous types of features, such as statistical features (Patange & Jegadeeshwaran 2021), wavelet features (Alamelu Mangahi & Jegadeeshwaran 2019), and histogram features (Natarajan 2017) are available. The present study focuses on the statistical features. Feature extraction is one of the techniques which is implemented to decompose the required signals as statistical features. Visual basic code is used to extract the statistical features (Aravind & Sugumaran 2017). There are several techniques, such as decision tree (DT) (Patange & Jegadeeshwaran, 2021), principal component analysis (PCA) (Lin, Pei, Ye, Guo & Wu, 2020), etc., are available for feature selection. In the present study, an attribute evaluator is suggested for selecting features.

The application of machine learning has been seen in many studies in the automobile sector. Jianhao Zhou, Jing Sun, Longqiang He, Yi Ding, Hanzhang Cao, and Wanzhong Zhao (2019) proposed a composite machine learning approach that predicted driver brake intention. They used CAN (Control Area Network) to collect data from real-life conditions and employed two algorithms ReliefF and

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RreliefF for analysis. Pajusco, Malhouroux-Gaffet, and Zein (2015) developed a modified SIC algorithm that yields faster results while searching for multipath properties of a given propagation channel. Jie Liu, Yan-Fu Li, and Enrico Zio (2018) worked on fault diagnosis of high-speed trains. They used an SVM (Support Vector Machine) framework with the selection of features, feature vector, model construction, and optimization of the decision boundary for their study. Albert Podusenko, Vsevolod Nikulin, Ivan Tanev, and Katsunori Shimoharac (2017) used many classifiers and genetic algorithms to build an intelligent classifier to find a solution for emergency braking classification from the accelerometer pedal's motion. They aimed at reducing the time lag between two cases: a) foot of driver moves from accelerometer pedal and b) driver presses the brake pedal to its full capacity. Rahul Kumar Sharmaa, V. Sugumaran, M. Amarnath and Hemantha Kumar (2015) worked on fault diagnosis of bearings using sound signals through the decision tree, Naive Bayes, and Bayes net algorithms. They compared the results and found that the decision tree gave the best results. Cerrada, Zurita, Cabrera, Sánchez, Artés and Chuan Li developed a robust system for diagnosing the faults in spur gears. They used random tree classifiers and genetic algorithms for their research and got a classification precision of over 97%. Alamelu Manghai and Jegadeeshwaran carried out fault diagnosis using machine learning of a hydraulic brake system through wavelet extraction from the vibration signals (2019). The features were classified using the best-first tree, Hoeffding Tree, SVM, and neural network classifiers. It was found of the algorithms used, the Hoeffding Tree algorithm provided the best classification accuracy of 94%. Many machine learning classifiers such as Naïve Bayes, Bayes net (Patange & Jegadeeshwaran, 2020), Fuzzy unordered rule induction algorithm (FURIA) (Alamelu Manghai & Jegadeeshwaran 2019), SVM, and PSVM (Tripathy, Rautaray, & Pandey, 2017), have been used for various condition monitoring studies. Naïve Bayes Updateable algorithm was found to have an accuracy of 84.61% in theme-based text classification (Saptono, Sulistyo, & Trihabsari 2016). Kumar, Sakthivel, Jegadeeshwaran, Sivakumar, and Kumar used the Hoeefding tree for predicting the engine parameter under various fuel blend conditions and achieved 98% accuracy in prediction (2019). Niranjan, Haripriya, Pooja, Sarah S, and Deepa et al proposed a hybrid technique using k-nearest neighbor and random committee algorithms for efficient classification of phishing (2018). However, a detailed study is required for applying these Machine Learning (ML) classifiers in fault prediction. Alamelu Manghai and Jegadeeshwaran (2018) studied the Logitboost algorithm for finding faults in a miniature prototype brake setup and achieved the maximum classification accuracy of 98.9%. However, the real time study based on these results has not been carried out. In this study, the ML classifiers such as Logitboost meta, Hoeffding tree, Random Committee, and Naïve Bayes updatable were used for classifying the brake faults. The effectiveness of the proposed algorithm will help to make the onboard diagnostic module. The paper is structured as follows:

1. Experimental Study: Different fault conditions were simulated on the real vehicle brake system and the corresponding vibration signals were acquired
2. Feature extraction from raw signals using VB code.
3. Feature selection using attribute evaluator
4. Feature classification using different ML classifiers.

2. EXPERIMENTAL STUDIES

The main objective of the study is to develop a model to monitor the brake condition. The condition monitoring study is carried out on a real vehicle brake system. The experimental procedures have been discussed in the subsequent sections.

2.1. Experimental Study

A commercial passenger LMV's hydraulic brake system was considered as the test setup as shown in Figure 1. Since hydraulic brakes are a prominent system in the medium motor vehicle like cars, to experiment with the components used in the real-world, branded vehicle (cars) parts were considered. The vibration signals are to be acquired from an experimental setup. The experimental set consists of two major parts. (i) Static road simulator; (ii) LMV with a brake setup. The main objective of the study is to investigate the effects of vehicle and road characteristics on dynamic forces applied by heavy vehicles on the brake system.

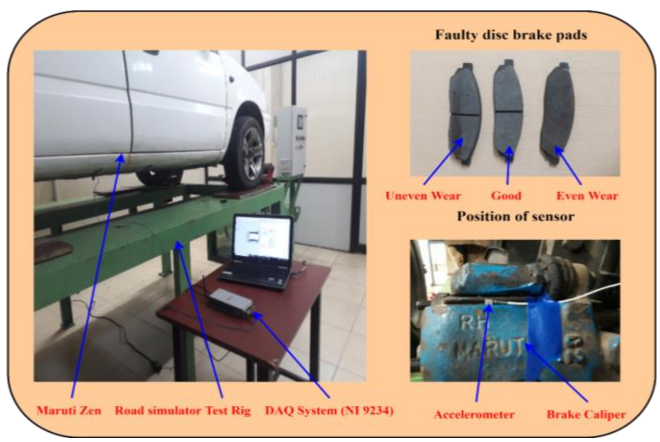

Figure 1. Experimental setup – Brake fault diagnosis

The static road simulator was designed using the hydraulic circuit which provides both static and dynamic testing environments for the analysis. The road simulator was used to test the vibration signal under static conditions. This will provide the standard signals under static conditions. The objective of this setup is to build the standard signal irrespective of the vehicle model. Vibration signals under various fault conditions were acquired using a piezoelectric type of uni-axial accelerometer with 10 mV/g sensitivity

(Figure 2(a)) and a Data acquisition card (NI 9234 with C9191 Wireless Chassis) (Figure 2(b)) through the LabVIEW graphical program (Figure 3).

Figure 2(a) IEPE type Accelerometer

Figure 2(b) Vibration DAQ (NI 9234) with wireless chassis (C9191)

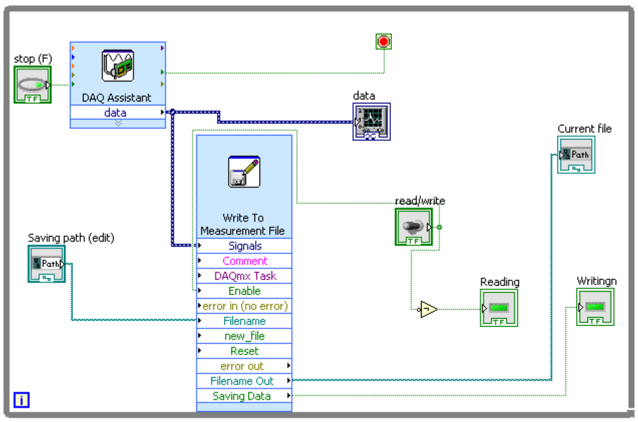

Figure 3. LabVIEW graphical program

2.2. Experimental Procedure

We have decided the driving scenario in to three categories. (i) City driving conditions (30 – 40 kmph); (ii) Moderate driving Condition (State Highways); (iii) Highway driving conditions (More than 80 kmph). In this study, to develop a generalized model, the city driving condition (speed 30km/hr) has been considered in this study. The drive shaft speed 331 rpm was calculated with the help tire radius and its angular velocity. If the tire speed is 331 rpm, the vehicle will travel in a 30kmph speed. Wheel speed and brake force create better impact on classification accuracy. High brake force creates less impact on classification accuracy when compared to the moderate/low brake force. At slow speed (331 RPM / 30km/hr), less brake force (28.7 kN) gives better classification accuracy. When the vehicle moves at this speed less brake force is enough to reduce / stop the vehicle. Hence the speed and brake force has been considered as 331 rpm and 27 N respectively. Initially, all the brake pad elements were assumed to be in good condition. The vibration signals were measured from the brake system under wheel speed 331 rpm and brake force 28.7 N). The vibration signals from an accelerometer mounted on the brake shaft were taken with the following settings:

1. Length of the sample: The minimum number of sample points (Sample length) in a data required for making a signal processing study should be 2n. Hence, the number of sample points has been chosen as 2^{10} (1024) in this study arbitrarily.
2. Frequency: 24 kHz, (Nyquist sampling theorem).
3. Number of samples: 55 trials.

The following six faults were simulated, and the corresponding vibration signals were acquired (Alamelu Manghai & Jegadeeshwaran, 2019). The captured vibration signals were processed for extracting information through feature extraction and feature selection.

(a) Air in brake fluid: By using a pump and hold method, atmospheric air is being sucked into the brake fluid.

(b) Brake oil spill on disc brake: 5ml of brake oil was applied to the brake disc using a Pasteur pipette.

(c) Drum brake pad wear: A drum brake pad of 7.50mm thickness was taken for the test. Using a cylindrical grinding machine thickness of both left and right pads was reduced to 5.70mm.

(d) Disc brake pad wear (even) - Inner: For this test, a brake pad with a thickness of 16.50 mm was chosen. Using a surface grinding machine thickness of the inner brake pad was reduced to 12.40mm.

(e) Disc brake pad wear (even) - Inner and outer: For this test, asbestos of thickness 16.50mm was chosen. Using a surface grinding machine thickness of the inner brake pad was reduced to 11.60mm, and the outer brake pad was minimized to 12.40mm.

(f) Disc brake pad wear (uneven) - Inner: For this test, a disc brake pad made of asbestos with a thickness of 16.50mm was chosen. The inner brake pad was machined Using a shaper machine, with a downward gradient (0.60) 15.12mm (big radius) - 14.72 (a small radius).

(g) Disc brake pad wear (uneven) - Inner and Outer: For this test, a disc brake pad of thickness 16.50mm was chosen. The inner brake pad was machined with a downward gradient (1.60) 14.76mm (big radius) - 14.12(a small radius) and the outer brake pad was machined with a downward gradient (0.60) 15.12mm (big radius) - 14.72 (a small radius).

The corresponding vibration signals were processed for extracting information through feature extraction and feature selection.

3. FEATURE EXTRACTION AND SELECTION

The captured raw vibration signal is in the time-domain which contains only the amplitude information. More information is required for getting a better learning model. Hence, preprocessing is necessitated to extract more information as features. Feature extraction is the process of computing certain information or measures that represent the signal (Aravind & Sugumaran 2017). The information can be extracted in two ways, namely decomposition and aggregating. Adding much information into a piece of single information is known as aggregating. Extracting more meaningful information from the raw signal is considered as signal decomposition. In this study, the signals are decomposed into twelve statistical parameters using a visual basic code.

Twelve sets of statistical parameters, namely range, skewness, kurtosis, sample variance, standard deviation, count, sum, maximum, minimum, mode, mean, median, and standard error were selected for this study objectively. These features were extracted using the visual basic code. Feature selection is a crucial step in machine learning that is used to either enhance the accuracy scores of estimators (classifiers) or to increase their performance in large-dimensional sets. Generally, the irrelevant feature input increases the computational cost which leads to overfitting. Hence, the researchers went ahead with the faster greedy methods such as attribute evaluator. The best feature set using a greedy-based attribute evaluator has been found by estimating the leave-one-out cross-validation (Jegadeeshwaran & Sugumaran 2015). In this paper, the attribute evaluator algorithm has been used to further enhance the efficiency by selecting the best feature sets. A better feature set was suggested by the greedy algorithm.

4. FEATURE CLASSIFICATION

Feature classification is a process of classifying the pre-processed data using a suitable machine learning model. Commercial brake system data can be trained and validated using suitable algorithms. The following meta-family classifiers were used in this study.

4.1. LogitBoost Meta Classifier

LogitBoost is a type of Meta family algorithm that applies logistic regression to the basic AdaBoost algorithm. Each iteration of regression fitting leads to the updating of the variable used. LogitBoost has been successfully used in tracing the chip data (Kim, Seo, Kang, Cho & Kim, et al 2015) and prediction of forest fire susceptibility (Tehrany, Jones, Shabani, Martínez-Álvarez & Bui 2019).

4.2. Hoeffding Tree Classifier

The Hoeffding Tree algorithm uses large data sets to learn from and uses the Heoffding Bound to split the features mathematically. It assumes the distribution by generating examples that are time-variant. The Hoeffding tree was successfully used in the medical field (Thaiparnit, Kritsanasung & Chumuang 2019).

4.3. Random Committee Classifier

The random committee classifier builds an ensemble of randomizable base classifiers. The straight-line average of predictions by each classifier is given as the final prediction output. In a study, the random committee along with ANN was used to predict the Electrical disturbance (Lira, De Aquino, Ferreira, Carvalho & O. N. Neto, et al 2007)

4.4. Naïve Bayes Updateable Classifier

The Naïve Bayes classifier is based on the Bayes theorem. The naïve part of the classifier's name refers to its assumption of independence between the features given. This classifier uses estimator classes and is the updatable version of the Naïve Bayes classifier. Naïve Bayes Updatable algorithm is generally faster compared to other algorithms. Said and Dewi reported the data classification using Naive Bayes Updatable classifiers (2019).

5. RESULTS AND DISCUSSION

In this current paper, fault diagnosis of the hydraulic brake system is taken and studied. The vibration signals were obtained under different simulated fault conditions from the experimental setup. Twelve statistical features are used to extract the information from the acquired vibration signals.

5.1. Effect of combined features on the classification accuracy

In this study, the feature selection is done using the effect of number of features study. We have 13 features that were extracted from each fault condition data. All the features may not be required for obtaining the maximum accuracy. Hence, the order of features will be helpful for identifying the maximum accuracy. In this study, the order of features was identified using the attribute evaluator. The attribute evaluator evaluates the weight of the contributing features through best first search method. Best first may search forward, backward, or search in both directions. Based on the outcome, the order (ranking) is decided. This order depends on the search methods that are used for identifying the contributing features. It considers the individual perspective ability of each feature and their redundancy degree for evaluation (Jegadeeshwaran & Sugumaran 2015). The subset of features that has low inter-correlation and that are highly correlated with class is chosen. The best first search methodology was adopted for attribute evaluators. Twelve features were fed in attribute evaluator and the contributing few features were identified through greedy best first search. Attribute evaluator suggests, the feature order, namely 1. Median, 2. Standard error, 3. Kurtosis, 4. Range, 5. Maximum, 6. Minimum, 7. Sample variance, 8.

Skewness, 9. Mode, 10. Standard deviation, 11. Sum, and 12. Mean. Based on this order, the contributing features were selected. Initially, all the twelve features were selected, and the corresponding classification accuracies were noted as shown in Table 1. Then, excluding the last feature (12. Mean), the corresponding classification accuracies were noted for the top 11 features. Similarly, leaving the 11th feature, the accuracy values are noted. In the descending order, the features were removed, and the accuracy value is noted in Table 1. Referring Table 1 LogitBoost meta gives the maximum accuracy when the number of features is seven whereas, for the Hoeffding tree it is six. Both random committee and naive bayes updatable have the maximum accuracy when several features are twelve.

Number of features	***Classification accuracy***			
	LBM[a]	***HT[b]***	***RC[c]***	***NBU[d]***
12	86.10	85.71	**87.83**	**86.87**
11	86.10	86.29	86.10	86.48
10	85.52	86.67	87.45	86.67
9	87.45	86.10	86.29	86.48
8	87.64	87.45	86.49	86.10
7	**88.22**	87.45	87.64	85.32
6	87.64	**87.83**	87.07	84.71
5	85.32	84.55	85.14	83.43
4	81.46	80.88	82.24	81.82
3	81.46	82.81	79.54	82.45
2	81.46	36.67	79.15	81.46
1	79.34	28.57	80.31	81.66

LBM[a]= Logitboost Meta, HT[b]=Hoeffding tree, RC[c]= Random Committee, NBU[d]= Naïve Bayes Updateable

Table 1. Effect of number of features on classification accuracy

5.2. Classification accuracy using Logit Boost Meta

Referring Table 1, LogitBoost Meta gave maximum accuracy when top seven features are used. The hyper parameters for which the maximum classification accuracy is obtained were identified using trial and error method. Logit boost used the following parameters: 1. Likelihood threshold: -1.7977; 2. Weight Threshold: 100; 3. Number of Iterations: 10. The performance of the classifiers used in the study is arranged in the form of a confusion matrix, given in Table 2. The guidelines on the interpretation of the square matrix are as follows. The first row in the confusion matrix represents the number of datasets that correspond to the “GOOD” condition. The first column stands for the number of data sets misclassified into other conditions (except the diagonal elements). The first element, i.e. the diagonal element denotes the number of datasets correctly classified under the “GOOD” condition. In the first row, of the 74 datasets that belong to the GOOD condition, two datasets are incorrectly classified into UDPWI (Uneven Disc Pad Wear (Inner)) condition.

Category	***a***	***b***	***c***	***d***	***e***	***f***	***g***
a	72	0	0	0	0	2	0
b	0	69	0	0	0	5	0
c	0	0	55	0	19	0	0
d	0	0	0	72	0	2	0
e	0	0	18	0	56	0	0
f	3	8	0	4	0	59	0
g	0	0	0	0	0	0	74

a -GOOD: Brake without any fault; b-AIR: Air in brake fluid; c- BOS: Brake oil spill; d-DPWI: Disc brake pad wear – Inner; e-DPWIO: Disc brake pad wear Inner & outer; f-UDPWI: Uneven disc pad wear (Inner); g- UDPWIO: Uneven disc pad wear (Inner & Outer).

Table 2. Confusion matrix for Logitboost statistical features

The element under column *‘f’* is non-zero, thus signifying a misclassification for this condition. In the row labeled ‘G’, all the 74 datasets are rightly classified under UDPWIO (Uneven Disc Pad Wear (Inner and Outer)) condition, with no misclassification. Hence, all the non-diagonal elements are zero. It can be drawn from the matrix that 74 samples in each class were considered for every condition of the brake system.

5.3. Classification accuracy, using Hoeffding Tree

Category	***a***	***b***	***c***	***d***	***e***	***f***	***g***
a	71	0	0	0	0	3	0
b	0	66	0	0	0	8	0
c	0	0	60	0	14	0	0
d	0	0	0	72	0	2	0
e	0	0	18	0	56	0	0
f	1	14	0	3	0	56	0
g	0	0	0	0	0	0	74

Table 3. Confusion Matrix for Hoeffding Tree

Among the 444 data belongs to all the fault conditions (Except 74 good data), 59 data are classified as faulty conditions itself which need attention. Even though it is misclassification, one fault condition is classified as other fault conditions. The classification accuracies of the various conditions were thus found in this manner and compared. The LogitBoost algorithm produced the maximum accuracy at 88.22%.

Twelve features were extracted using the feature extraction techniques. The algorithm provides the maximum accuracy with six features. The classification accuracy is found using the Hoeffding bound. The algorithm also uses the Gini information for splitting. Hoeffding tree used the split threshold as 0.05 and the number of instances is 200. The top six features were used for obtaining the maximum classification accuracy. The classification results have been given in Table 3. The Hoeffding tree produced the maximum accuracy as 87.83 %. In his study also, among the 444 data belongs to faulty conditions, 60 data are misclassified other fault cases that also need attention.

5.4. Classification accuracy using Random Committee

Twelve features were extracted using the feature extraction techniques. The algorithm provides the maximum accuracy 87.83 % with six features. The top six features were used for the classification. The classification results have been given in Table 4. Random committee uses the random number seed. The number of iterations for which the maximum accuracy was obtained is 10. Random committee used the Random tree as base classifier.

Category	***a***	***b***	***c***	***d***	***e***	***f***	***g***
a	71	0	0	0	0	3	0
b	0	67	0	0	0	7	0
c	0	0	59	0	15	0	0
d	0	0	0	73	0	1	0
e	0	0	12	0	62	0	0
f	2	10	0	5	0	57	0
g	0	0	0	0	0	0	74

Table 4. Confusion matrix for Random Committee

5.5. Classification accuracy using Naïve Bayes Updateable

All the twelve extracted features are used for classification accuracy. NB algorithm produced 86.87 % classification accuracy with all the features. Naïve bayes updatable uses kernel estimator for calculating the value. The algorithm used supervised discretization for obtaining the maximum accuracy.

Category	***a***	***b***	***c***	***d***	***e***	***f***	***g***
a	72	0	0	0	0	2	0
b	0	65	0	0	0	9	0
c	0	0	60	0	14	0	0
d	0	0	0	74	0	2	0
e	0	0	22	0	52	0	0
f	3	15	0	3	0	53	0
g	0	0	0	0	0	0	74

Table 5. Confusion matrix for Naïve Bayes Updateable

The classification accuracy for the NBU algorithm is shown in Table 5.

5.6. Comparative Study

Referring Table 2 to Table 5, the data belongs to AIR (Air in brake fluid), BOS (Brake oil spill), DPWI (Disc brake pad wear – Inner), DPWIO (Disc brake pad wear Inner & outer), UDPWI (Uneven disc pad wear (Inner)) is having the similar kind of misclassification. For example, the few data belong to AIR is misclassified as UDPWI by all the four considered classifier model. There is a difference in the number of data only. The same trend is also seen in all other cases like BOS, DPWI, DPWIO, UDPWI. Some of the data have the similar kind of vibration signatures for the misclassified class. This may lead to misjudgment on the fault prediction. The data must be properly acquired for getting the accurate results.

The classification accuracy of various algorithms is summarized in Table 6. All the extracted features were classified using the various machine learning classifiers. Initially, the default parameters were used for the classification. Then the hyper-parameters were identified using the trial-and-error method for obtaining the maximum prediction accuracy. Among the considered algorithms, LogitBoost Meta gives the maximum classification accuracy. Since, LogitBoost is a boosting algorithm, it is used to increase the classification accuracy in meta learning. The Logitboost algorithm changes the loss function through binomial log-likelihood. Hence, the Logitboost algorithm tends to be less sensitive to outliers and noise. Hence, the LogitBoost algorithm has shown improved generalization capability applied to the improved data reduction of the training set, along with enhanced computational performance and simplification.

S.NO	**Name of classifier**	**Classification accuracy (%)**
1	**Logitboost meta**	**88.22**
2	Hoeffding tree	87.83
3	Random committee	87.83
4	Naive bayes Updateable	86.87
5	Bagging	85.33
6	Filtered Classifier	85.52
7	Iterative Classifier Optimizer	86.87
8	Linear Support Vector Machine	85.50
9	Cubic Support Vector Machine	85.70

Table 6. Maximum classification accuracy of different Meta family algorithms

The results of all four algorithms have been compared to the results of other standard classifiers such as bagging, filtered classifier, linear and cubic support vector machines and

Iterative classifier optimizer. The comparative study also reveals the performance of the LogitBoost algorithm towards the brake fault prediction.

6. CONCLUSION

The paper focuses on the fault diagnosis of automobile brakes using artificial intelligence based on vibration signals. A hydraulic brake setup was constructed and seven fault conditions were identified which were then simulated on the setup. Twelve sets of features were selected and various algorithms (Logit Boost Meta, Hoeffding Tree, Random Committee, and Naïve Bayes Updateable). Of 74 samples, Logit Boost Meta correctly classified 88.22% of the samples. Hence Logit Boost algorithm is given as the best algorithm for the brake fault classification. Moreover, this study was done under constant speed and constant brake force. The same can be experimented on various speed ranges from 20 kmph to 100 kmph. The same procedural steps can be adopted under various operating conditions for developing generalized ML models. If the driver knows the status of the brake during running, it will be very helpful to avoid several accidents due to brake failures. This can be achieved through a Graphical user Interface (GUI). The future scope of this study would be the development of a GUI in which the brake condition will be notified to the driver.

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