Contribution to bearing diagnosis using Ensemble Learning techniques

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Abstract: The rolling element bearing is a key component in many mechanical installations, and diagnosing its faults is crucial in the field of predictive maintenance. The objective of this work is to propose a diagnostic technical method for rolling element bearing faults that employs Ensemble Learning model such as Adaptive Boosting (AdaBoost) classifier. The proposed method includes Preprocessing of vibration data with fast Kurtogram; Extracting statistical features such as Mean, Standard Deviation, and Kurtosis; Training the Ensemble Learning algorithms for classifying the various faults based on extracted features. the results verify the effectiveness of the method in extracting fault characteristics and diagnosing faults of bearings.

Keywords: Predictive maintenance, Diagnosis, Vibratory analysis, Kurtogram, Time domain feature, Ensemble Learning, Adaptive Boosting.

1. INTRODUCTION

Predictive maintenance (PdM) has become a crucial pillar in many modern industries because it enables the optimization of maintenance costs, increases productivity, and ensures more reliable and durable operations. In an evolving economic environment, competition forces industrial companies to enhance the performance of their production assets to meet customer demands. Due to its direct impact on production equipment, maintenance has become a significant performance lever in determining organizational outcomes. Implementing a predictive maintenance plan optimizes maintenance operations and ensures they are carried out at the right time, with the ultimate goal of ensuring product quality and improving equipment availability rates.

Dynamic and rotating machines, due to their construction and robustness, find a wide range of applications in the industrial domain. All machines in operation produce vibrations, which are reflections of the forces exerted by moving parts. Predictive maintenance monitors the vibrations of rotating machines with the aim of detecting emerging issues and preventing catastrophic failures. Deterioration in performance often leads to increased vibration levels. By observing the evolution of these levels, valuable insights into the machine's condition can be obtained. The current trend is to seek tools that enable early detection of defects, gradually replacing traditional system maintenance with predictive maintenance. This is why system monitoring and diagnostics have become one of the main concerns for manufacturers and operators. Rotor faults, stator faults, rolling element bearing (REB) faults, and other faults commonly occur in machines, among them bearing faults are most frequent. Statistics shows that 40% of total breakdown situation in large size machines occurred due to bearing fault and the number is as high as 90% in case of small machines (Thorsen, 1995). The main elements of a bearing are the inner, and outer ring, rolling element, and cage. Faults in bearings may occur during manufacturing or after some period of operation. Such failures could cause financial losses or human causalities (Nishat Toma & Kim, 2020).

Bearings are a crucial component of machines used across various industries, and their reliable operation is critical for an organization to robustly maintain its supply chain. Unplanned downtime of machines leads to revenue loss, lowered productivity, and missed production targets which in turn adversely affects an organization's ability to meet its obligations leading to a reputation and other risks. However, bearings are prone to failure for a variety of reasons, including material defects, poor installation, wear, and corrosion. Anticipating bearing failures beforehand and preemptively replacing them to prevent substantial damage to the machinery can effectively reduce both maintenance expenses and capital costs. Vibration signals obtained using a variety of accelerometers are widely used to monitor and assess the health of systems (Abburi et al., 2023).

Vibration signals obtained from bearings contain abundant information regarding machine health conditions. Consequently, vibration-based methods have undergone intensive study over the past few decades. It is possible to obtain vital characteristic information from the vibration signals through the use of signal processing techniques (Lei et al., 2007). In order to effectively diagnose faults occurring in rolling element bearings, researchers have extensively investigated different signal processing techniques to extract fault characteristics from vibration signals. Since the envelope analysis focuses on the high-frequency broadband signals characterizing bearing conditions and may minimize the effects of interfering signals within the selected frequency band, it has been widely applied in detecting faults of rolling element bearings (Lei et al., 2011). kurtogram, as an envelope analysis technique, was originally presented by Antoni (Antoni, 2007) and Antoni and Randall (Antoni & Randall,

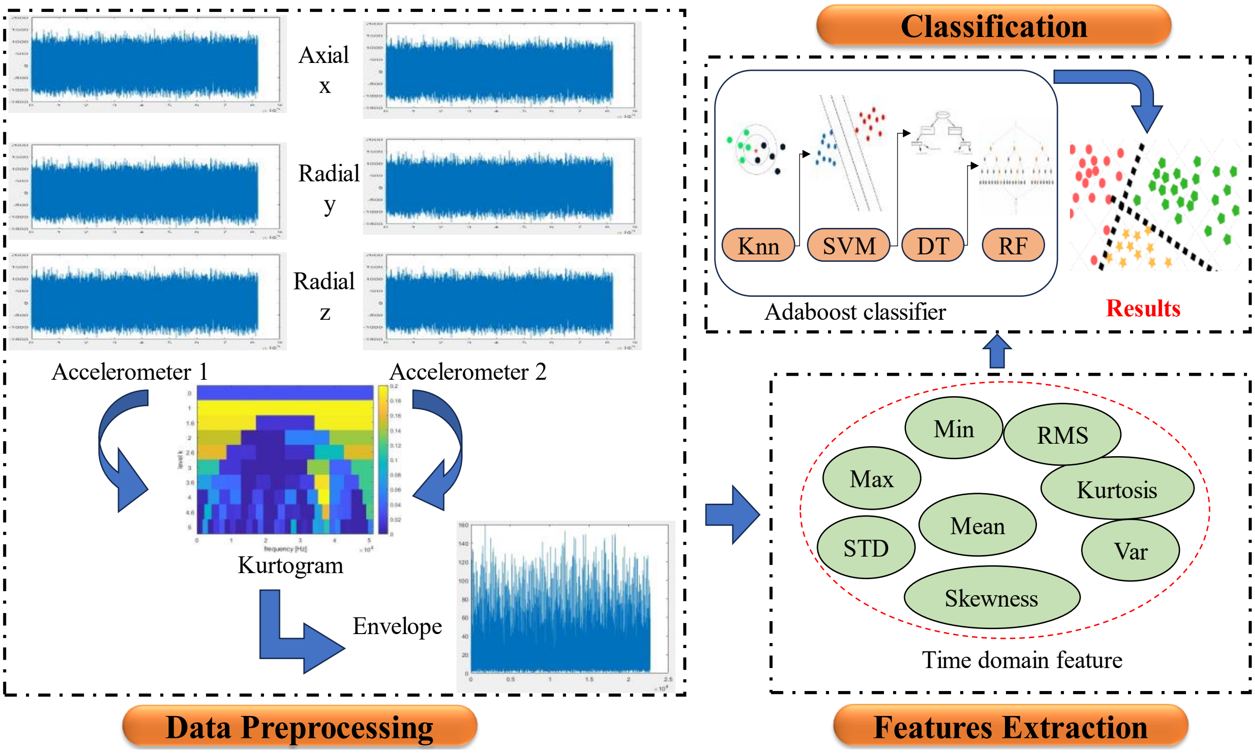


Figure 1. The proposed method.

2006) made a very thorough and interesting study on SK; first they generalized it and proposed the definition of the ‘‘kurtogram’’ to a wider class of non-stationary signals. Due to its superior capability in extracting transient components hidden within noisy signals, the kurtogram has proven to be a highly potent and practical tool in machine fault diagnosis (Antoni, 2007). Kurtogram based on the short time Fourier transform (STFT) or FIR filters, which improves the performance improvement of the kurtogram in extracting transient characteristics from a noisy signal and identifying faults (Lei et al., 2011). Kurtogram approaches have been widely adopted in recent years for Data Preprocessing. For example, (Geng et al., 2020) is used kurtogram to further enhance the robustness of the results to variable operating conditions and noises. The method proposed by (Afia et al., 2018) is tested and compared to the fast kurtogram for the diagnosis of gearbox faults using experimental vibration signals. (Lei et al., 2011) proposes an improved kurtogram method adopting wavelet packet transform (WPT) as the filter of kurtogram to overcome the shortcomings of the original kurtogram (introduces WPT into kurtogram). Among the different data preprocessing techniques, (Aburakhia et al., 2022) and (Lourari et al., 2024) used wavelet packet decomposition (WPD) to increase system robustness and signal denoising.

In recent area of maintenance Machine Learning algorithm are practiced by researchers for fault diagnosis and prognosis. Machine learning (ML) based fault diagnosis has proved by several researches and convinces its benefits in automated condition monitoring. (Nishat Toma & Kim, 2020) have present bearing fault detection by using the Ensemble Learning (EL). Two classifiers random forest (RF) and extreme gradient boosting (XGBoost) are trained and tested using the extracted feature set to classify the bearing fault condition. Both classifier models exhibit highly promising results in terms of accuracy and other accepted performance indicators. (Patil, 2020) have characterized the diagnosis procedure of ball bearing by using six EL technique such as, Random Forest (RF), Extra tree (ET), Adaptive Boosting (AdaBoost), Gradient boosting (GB), extreme gradient boosting (XGBoost), and Majority Voting. Majority Voting ensemble technique outperforms all individual base ensemble classifier and gives the best performance. Recently, (Panagou et al., 2022) have used XGBoost classifier for investigation of important sensors was performed in a steel industry production line. Sensors strategically tracks gearbox and shafts.

After this introduction and state of the art, in this article we focus on the kurtogram technique (for data preprocessing) and Ensemble Learning techniques (for classification). In the following section we present Methodology and diagnostic approach. The third section summarizes experimental setup while Section four discusses the results. Finally, a conclusion and perspectives close this work.

2. METHODOLOGY AND DIAGNOSTIC APPROACH

The proposed methodology represents a crucial aspect of Diagnosis and Predictive Maintenance, focusing on Rolling Element Bearing health monitoring, and decision support. The overall framework is shown in Figure 1.

2.1 Data Preprocessing using the fast kurtogram

The fast kurtogram (FK) is an optimized version of the Kurtogram designed to reduce computation time, FK determines the frequency band with the maximum spectral kurtosis (SK). In this section, we briefly introduce basic principles of the fast kurtogram.

Kurtosis detects the impulsivity faults related to rotating machines by computing the peaked ness of the data signal. Spectral kurtosis (SK) is a measure that evaluates kurtosis, indicating how the impulsiveness of a signal varies with frequency. As noted, faults associated with rolling element bearings give rise to modulated impulses. The SK value is obtained by calculating the kurtosis value for each frequency band to extract its impulsive and non-stationary components, then find their location in the frequency domain as is expressed in (Afia et al., 2018):

$$K_x(f) = \frac{\langle |H(t,f)|^4 \rangle}{\langle |H(t,f)|^2 \rangle^2} - 2 \qquad (1)$$

With $H(t,f)$ represents the time-frequency complex envelope of the analyzed signal, and it is calculated with short-time Fourier transform; and < > denotes averaging operator.

The SK will be large in frequency windows where the fault signal is dominant.

Fast kurtogram was proposed by (Antoni, 2007) is a fast algorithm to compute kurtogram. Due to the advantages in detecting, characterizing and locating transient signals hidden in signals, fast kurtogram have proven to be an effective and practical tool in rotating machinery fault diagnosis due to their advantages in detecting. For example, when using envelope analysis to diagnose, the center frequency and bandwidth of the optimal band-pass filter can be determined with fast kurtogram. An example is shown below in Figure 2. It is a fast kurtogram image of a sample. Fast kurtogram graph is used to display spectral kurtosis (SK) values of different frequency bands in frequency domain. In the FK image, each colored block represents a frequency band. The color of a colored block represents the SK value of the frequency band (Bw), the width of the block represents the bandwidth, and the position of the block in the abscissa represents the center frequency (fc). The block with the highest SK value will tell the

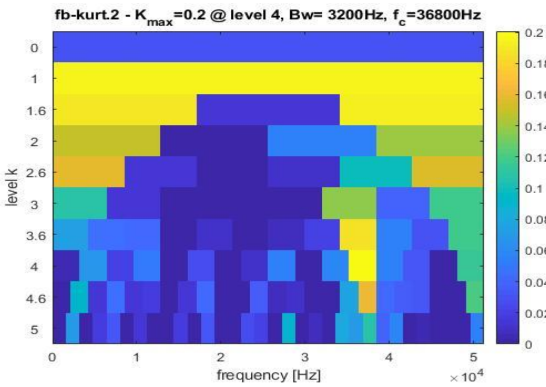


Figure 2. Sample of the fast kurtogram.

parameters of the optimal band-pass filter. The parameters of the optimal bandpass filter are determined. Then use envelope with the filter to diagnose.

2.2 Features extraction

Feature extraction is critical to degradation assessment because bearing vibration signal contains rich hidden information. Numerous time-domain features are utilized to explore the relationship between the bearing running states and vibration signals. Among them, RMS and kurtosis are most common features, since they can effectively reflect the real-time change of the bearing vibration. However, the fluctuation caused by the uncertainty of vibration has a great influence on the estimation of the bearing degradation. Therefore, further processing of the traditional features, e.g., feature fusion or statistical analysis, is needed to find a good indicator (Zhang et al., 2019).

Given the complex working conditions of bearings, a single feature index offers limited information for characterizing the bearing degradation. Therefore, 10 time-domain feature indexes of bearing vibration signal data are extracted. For details, see Table 1.

Table 1. Time domain feature parameters

Feature	Calculation Formula
Minimum value	$\min x(N)$ (2)
Maximum value	$\max x(N)$ (3)
Mean value	$\bar{x} = \frac{1}{N}\sum_{i=1}^{N}(x_i)$ (4)
Peak to peak	$xmax - xmin$ (5)
Standard deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2}$ (6)
Root mean square	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\lvert x_i \rvert)^2}$ (7)
Skewness	$\frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^3}{\sigma^3}$ (8)
Kurtosis	$\frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\sigma^4}$ (9)
Variance	$\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2$ (10)
Entropy	$-\sum_{i=1}^{N} P_i . \log_2 P_i$ (11)

With x(N) is the envelope signal, N represents the number of samples taken from the signal, $\bar{x}$ the mean, P is the probability.

2.3 Ensemble learning model for fault diagnosis

Recently, the selection of an effective machine learning algorithm has become pivotal for achieving high performance in fault diagnostic models. Ensemble learning algorithms are one of the approaches that provide better performance than any single prediction algorithm (Martínez-Álvarez et al., 2015). This technique permits the higher predictive performance. Bagging (Random Forest), Boosting (Gradient Boosting, AdaBoost), and Stacking are the types of ensemble technique explained as follows. In ensemble learning, multiple weak learners work together to produce a better model achieving higher accuracy. Some ensemble learning algorithms such as AdaBoost may achieve higher accuracy than artificial neural networks (Chakraborty & Elzarka, 2019).

Ensemble learning techniques will combine the results from individual models to enhance the classification performance of the entire model. In our study, two ensemble learning algorithms known as Random Forest and AdaBoost were investigated for classification, for AdaBoost we used four classifiers (K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF)).

Bagging (Random Forest): is a popular ensemble learning technique used in machine learning. involves the process of training several independent classifiers and then combining the outcomes of each individual classifier to make the final decision. The decision is made based on majority voting in classification problems and average is considered in regression. Random forest is one of the well-known techniques of bagging. The Random Forest (RF) algorithm is a collection of decision tree, where each tree is individually trained on an arbitrarily selected independent training dataset. In Random Forest (RF), each tree is trained on a separate sampled subset of the input dataset, and the distribution rate is the same for all trees. RF demonstrates exceptional performance not only in classification and regression, but also shows outstanding performance in variable selection. The trees are obtained from the combination of datasets with bootstrap subsampling and various subsets of features for splitting at every node (Nishat Toma & Kim, 2020). The Random Forest (RF) model involves a splitting process where a single node is divided into two or more nodes, the final output of the model is determined through a majority voting process.

Boosting: is another popular ensemble learning technique used in machine learning. It is a technique of changing weak classifier into strong classifier. Unlike bagging, which trains multiple models independently and then combines their predictions, boosting trains multiple models sequentially, with each model correcting the errors made by its predecessors. Also, boosting algorithms are generally more computationally expensive compared to bagging because models are trained sequentially. Boosting algorithms differ in how they assign weights to the training instances and how they combine the predictions of individual models. Some popular boosting algorithms include AdaBoost (Adaptive Boosting), Gradient Boosting Machines (GBM), XGBoost, LightGBM, and CatBoost.

3. DATASET DESCRIPTION

The data were collected over a rig set up at DIRG Lab in the Department of Mechanical and Aerospace Engineering at Politecnico di Torino, specifically conceived to test high speed aeronautical bearings, whose accelerometric acquisitions at variable rotational speed, radial load and damage level, together with temperature measurements, are being made available as open access data: Two different experimental sections were obtained in this database (Daga et al., 2019). In the first the accelerations are relative to bearings with different damages, running at different speeds and under different loads. We are interested in the 2nd section of the database, the behaviour of a single damaged bearing undergoing a long (about 330 hours (h)) test at constant speed and load. The test rig contains the accelerations of the two most significant points of the structure, A1 and A2 in Figure 3, located respectively on the support of the damaged bearing under test B1 and the support of the larger bearing dedicated to the application of the external load B2.

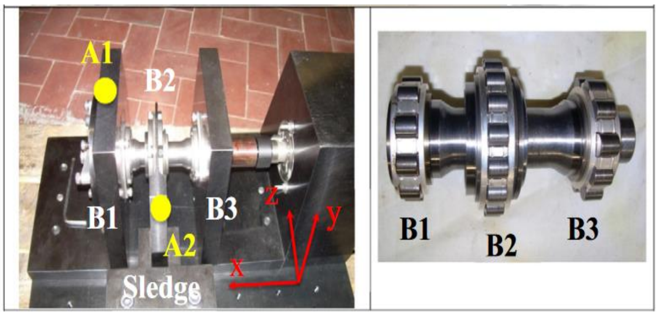


Figure 3. Positions of the two accelerometers and the reference system (Daga et al., 2019).

An endurance test has been performed on bearing B1 (defect on a roller) to monitor the evolution of the defect, initially a conical indentation with a maximum diameter of about 450 mm. The evolution of the defect has been inspected also after 70, 144 and 332 h of the endurance test, every measurement of the endurance assessment has been performed at the same conditions:

- Nominal speed: 300 Hz (i.e. 18,000 rpm).
- Nominal load: 1800 N.

The time histories of two triaxial accelerometers have been regularly recorded and each registration lasts for 8 s with a sampling frequency of 102.4 ksps. Each file contains a matrix with the same name of the file (apart from the .m extension) with 819,200 rows (time samples) and 6 columns (one for each channel).

4. RESULTS AND DISCUSSION

In this study, the vibration data is collected from the DIRG lab of Politecnico di Torino dataset (Daga et al., 2019) for a long (about 330 h) test at constant speed and load of a single damaged bearing undergoing. The data is collected from the measurements of the sensors, is in the form of 66 files in MATLAB “. mat” format is shown in Table A2 in Appendix A of (Daga et al., 2019).

The experimental signals after 70, 144 and 332 h are shown in Figure 4.

It can be seen that it is not possible to detect the bearing failure only by looking at the waveform, since the fault impulses are masked by the noise. To overcome this problem, we first applied FK on the vibration signals recorded with a sampling frequency of 102.4 kHz.

4.1 Data Preprocessing and features extraction

The kurtogram function offers essential insights useful for Spectral Kurtosis analysis. It computes the spectral kurtosis across various window sizes utilizing a fast kurtogram algorithm. Along with the kurtogram and its associated frequency and window vectors, the kurtogram function provides the optimal window size along with other filter-tuning parameters, and it offers visualization capabilities to illustrate the results of its computations.

The fast kurtogram algorithm uses bandpass filtering along with a simplified computation to approximate the spectral kurtosis for each window size and frequency rather than compute the short-time Fourier transform (STFT) as the higher-fidelity kurtosis does. Additionally, it decreases the number of iterations necessary for the algorithm to cover the frequency-window plane compared to the full kurtogram method.

Figures 5 show the FK after 70, 144 and 332 h, respectively.

Figure 5(c) displays the color map of FK after 70 h, the bandwidth and center frequency are equal to 6400 and 48000 Hz, respectively, while Figure 6 displays the filtered signal envelope of that band.

After pre-processing the vibration data, statistical features were extracted from the pre-processed vibration signal (fast kurtogram envelope) in time domain.

Then, the extracted Statistical features were given as inputs to the ensemble learning techniques for multi-class classification.

4.2 Classification

Based on our data the following classifications were made:

- class 1: Less serious defect (after 70 h)
- class 2: Very serious defect (after 144 h)
- class 3: Unacceptable (after 332 h)

Before start learning, it is necessary to divide the feature matrices into two parts, one part contains 70% of data for

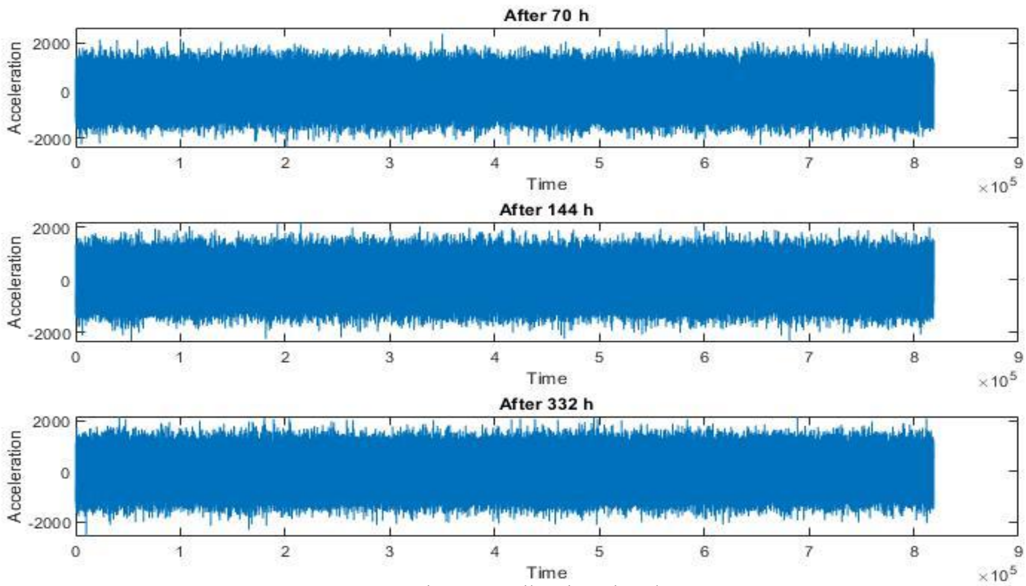
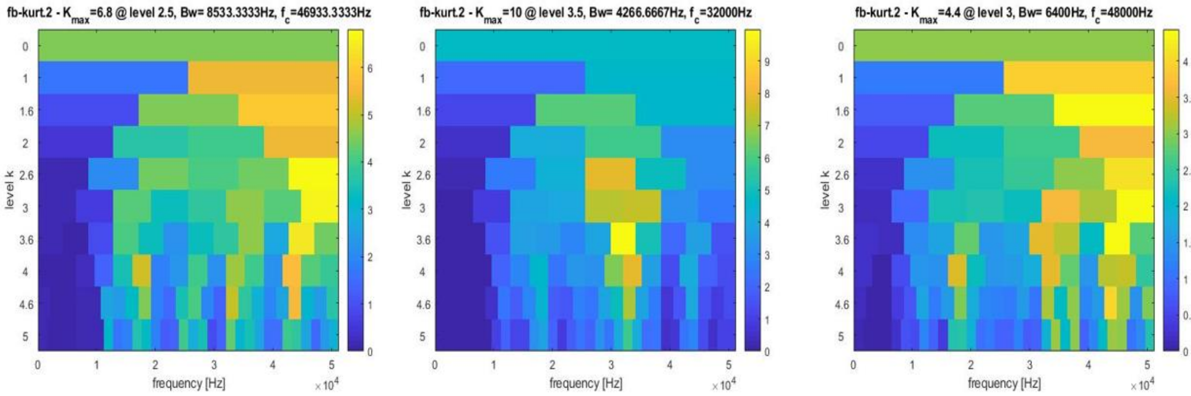


Figure 4. Vibration signals.



(a) After 70 h **(b) After 144 h** **(c) After 332 h**

Figure 5. Fast kurtogram of the vibration signals.

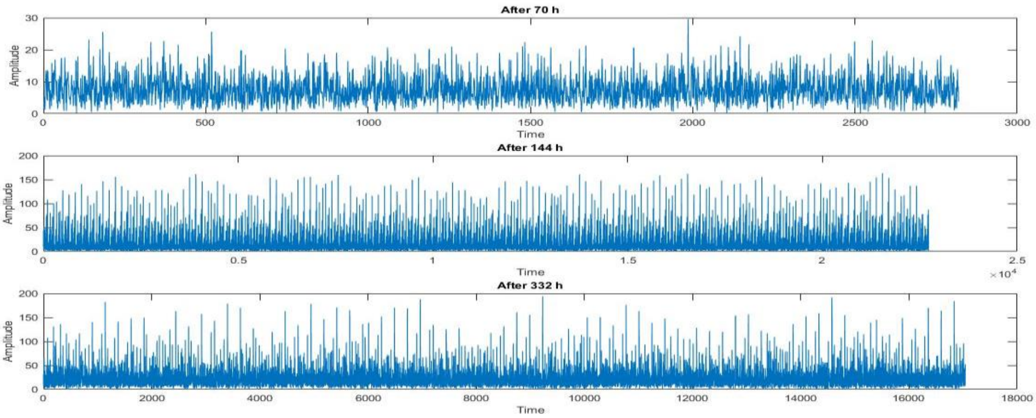


Figure 6. The envelope signals.

training and the rest will be for testing. In our case, we used validation by holdout.

In this study, three machine learning models (ML) and two ensemble learning techniques (EL) are performed, such as:

- Machine Learning:

1. K-Nearest Neighbours (KNN): Number of Neighbors= 5
2. Support Vector Machine (SVM): Linear SVM
3. Decision Tree (DT)

- Ensemble Learning:

1. Random Forest (RF): Number of Trees= 200
2. AdaBoost: is the method proposed in this paper, we used KNN (Number of Neighbors= 5), Linear SVM, DT, RF (Number of Trees= 50), and RF (Number of Trees= 200) respectively.

4.3 Results

The utilization of a confusion matrix is a valuable approach to assess model performance, particularly for multi-class problems. The confusion matrix presents a detailed representation of the correctly classified TP values, FP values that are categorized in the wrong class, false negative (FN) values that belong to the incorrect class, and correctly classified TN values in the other class. To measure the effectiveness of a model, several commonly used performance metrics are calculated from the confusion matrix, including Accuracy, LOSS, Precision. These metrics are derived from equations formulated using the confusion matrix, facilitating a precise evaluation of the proposed model's effectiveness (Shehzad et al., 2023).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{12}$$

$$LOSS = 1 - Accuracy \tag{13}$$

$$Precision = \frac{TP}{TP + FP} \tag{14}$$

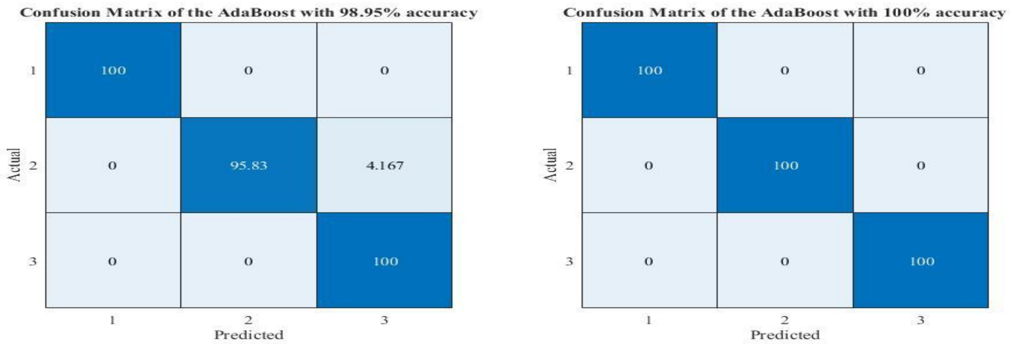


Figure 7. Confusion matrix of the AdaBoost for two tests with minimum Accuracy and maximum Accuracy.

Over 10 tests, the Accuracy (ACC) of each model was recorded. We calculated the minimum Accuracy, maximum Accuracy, Standard Deviation Accuracy, and mean Accuracy as listed in Table 2, in order to determine the most accurate and stable model among the five models.

Table 2. Accuracy results of different models

Tests	Knn	SVM	DT	RF	AdaBoost
Test 1	91.66 %	97.91 %	97.91 %	98.95 %	100%
Test 2	93.70 %	100%	100%	100%	100%
Test 3	92.70 %	96.87 %	97.91 %	98.95 %	100%
Test 4	91.66 %	96.87 %	95.83 %	97.91 %	100%
Test 5	94.79 %	97.91 %	98.95 %	100%	100%
Test 6	95.83 %	100%	98.95 %	100%	100%
Test 7	96.87 %	100%	100%	98.95 %	100%
Test 8	96.87 %	98.95 %	97.91 %	98.95 %	100%
Test 9	92.70 %	97.91 %	100%	97.91 %	100%
Test 10	95.83 %	98.95 %	97.91 %	98.95 %	98.95%
Minimum ACC	91.66 %	96.87 %	95.83 %	97.91 %	98.95%
Maximum ACC	96.87 %	100%	100%	100%	100%
Mean ACC	94.27 %	98.54 %	98.54 %	99.06 %	99.89%
Standard Deviation ACC	2.03	1.22	1.31	0.76	0.32

The AdaBoost classifier was found to have an average Accuracy of 99.89% and a Standard Deviation of 0.32, which implies good stability and high performance.

For a better representation of performance, it is preferable to represent the Confusion Matrix, which will give us the classification Accuracy of each class. Figure 7 shows the confusion matrix of the AdaBoost for two tests with Minimum Accuracy (98.95%) and Maximum Accuracy (100%).

In our study, the results obtained demonstrate the effectiveness of the data preprocessing method using fast kurtogram, which aimed to enhance the data quality by eliminating undesirable or irrelevant elements, potentially leading to improved performance of machine learning models. After examining the stability and accuracy of classification techniques, it is noted that the best classifier in our case is AdaBoost.

5. CONCLUSION

In this study, a data-driven approach using a vibration signal analyzed by fast kurtogram and Ensemble Learning methods was proposed for bearing fault diagnosis. We included the data preprocessing technique to improve the data quality and increase system robustness and signal denoising. A Time domain feature parameters was also utilized for feature extraction from rolling signals. The proposed ensemble learning model achieved a 99.80% accuracy score on the test set. Further, results demonstrate the capability of Ensemble Learning-based approaches in achieving very high accuracy with moderate computational requirements compared to machine learning-based methods. Moreover, the results indicate that using fast kurtogram features with Ensemble Learning would lead to better performance.

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