Vibration-based fault detection and classification in ball bearings using statistical analysis and random forest

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ABSTRACT

In this paper, a study on the fault diagnosis of ball bearings was done with a vibration dataset. The bearing conditions are classified through the extraction of different statistical features from time-domain vibration signals. The dataset consists of mean, median, standard deviation, skewness, kurtosis, dominant frequency (all features obtained from wavelet transform on the original dataset), and the class label (1 if the bearing is healthy, and 2 if the bearing is faulty). The research paper has conducted seven kinds of fault cases to be studied and applied machine learning strategies to diagnose these faults, mainly using a Random Forest model. Correlation matrix analysis describes the associations among features and shows a strong association between some features and the independent impact of others. The Random Forest model attained an accuracy of 90.42%, clearly revealing the robustness of the proposed method. The confusion matrix gives the model performance in detecting the various fault conditions.

Keywords: Ball bearings, fault detection, vibration analysis, statistical features, machine learning, random forest

1. INTRODUCTION

Ball bearings in many applications, have become the most critical mechanical constituent. We all encounter these daily as motors, turbines, compressors, and vehicles. To ensure that those machines work correctly, ball bearings reduce the friction between the moving parts. The potential consequences of ball bearing failure can be severe, such that drastic downtime, expensive repair, and even safety hazards can be improved by earlier and more accurate detection of faults when needed for equipment to run with efficiency and high reliability[1,2]. These conventional fault-detection techniques mostly rely on physical inspection and fundamental signal analysis and are inadequate. They turn out to be sometimes too cumbersome, laborious, and not capable of fault detection at its nascent stage. Besides, most of these techniques often fail to exhibit the complete dynamics of bearing faults under changing operational conditions. Therefore, there exists a current demand for more sophisticated diagnosis techniques having correct, efficient, and least manual interventional strategies in the field of diagnosis of bearing faults. Condition in the bearings significantly reflects on the performance and reliability of rotating machinery. Detecting faults in such vital components is essential to avoid breakdowns and ensure smooth running[3-5]. The performance and reliability of rotating machinery heavily depend on the condition of its bearings. Combined vibration analysis with artificial intelligence scripting is one of the most potential methods of fault diagnosis because it gives more accuracy and efficiency and thus is considered to be effective[6-8]. Zhang et al. (2015)[9] also recommended an intelligent way for roller bearing fault diagnosis. The method implemented was an incremental support vector machine with a multivariable ensemble. This approach significantly improved the accuracy of the process of fault classification using vibration signals. Real-time data incrementally emerges in online monitoring systems, and the ensemble-based method deals with such an incremental nature of real-time data. In the same context, ANNs and wavelet transform techniques in rolling element bearings' fault diagnosis have been used by Gunerkar et al. Gunerkar et al. (2019)[10] for fault conditions through vibration signals can be clearly identified under the proposed method; this is because it adequately follows a given procedure. The ability of ANNs to effectively handle non-linear and complex data associated with vibration is evident through the analysis, in which it forms a potent tool for fault

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Almounajjed et al. (2021)[11] highlighted a review with the main points of some state-of-the-art machine learning algorithms used for fault diagnosis tasks related to the isolation and classification problems in rolling bearings and industries, with emphasis on the application of AI techniques in processing and analyzing vibration signals associated with faults detection and condition monitoring. Now, we address the adaptability and flexibility of machine learning algorithms across varied industrial applications.

In their paper, Senthilnathan et al. 2024[12], reviewed developments in methods for diagnostic imperfections of the spheric roller bearing. The authors elaborate on several techniques for signal processing and artificial intelligence to filter noise and enhance an accurate fault diagnosis. This literature will help us understand the current trends and challenges in the field. Despite considerable advances, several fault diagnosis issues remain. One of the main issues is noisy data and changing operating conditions. Acknowledging these limitations, hybrid models and ensemble methods based on multiple machine-learning methods are studied here for better diagnostics[13-15].

This paper reports an overall outcome of the vibration data characterization and estimation of fault size. It emphasizes that more robust output can be obtained when we combine various techniques. The main objective is to develop an effective and accurate methodology for fault diagnosis in ball bearings with vibration data and statistical feature extraction. The objectives of the work specifically include the extraction of various remarkable statistical features from vibration signals to find unique patterns related to different fault conditions, training and testing of a Random Forest model for bearing condition classification, and its evaluation in standard metric model terms and open discussion concerning feature importance and their correlation concerning the fault diagnosis test and final validation through a large-scale experiment together with possible improvements. The results and discussion and the conclusion follow the methodology sections. References and appendices bringing out supplementary information join the main sections of this paper.

2. METHODOLOGY

2.1 Experimental work

The bearings have been tested using the FALEX multispecies test bench, available in the Tekniker lab[16]. In situ, the design and manufacturing of bearing faults took place in the DLR lab. The FALEX test bench has undergone essential modifications to integrate an in-depth monitoring infrastructure of forces, speed, temperature, vibration sensors, and a data acquisition system. The bearing test rig Figure 1 is fitted with three accelerometers model PCB 356A32 to measure triaxial vibrations along the *x*-, *y*-, and *z*-axes. Acceleration data was gathered at a 25.6 kHz sampling frequency. The bearing under test was installed in the vertical position in the test rig, and a vertical axial load was given to the inner race to make a simulation typical of the load and speed conditions for electro-mechanical aerospace systems. The setup of the experimental test bench FALEX enabled in-process monitoring of various parameters. It ensured exact control and accurate acquisition due to the created bearing faults having further very small vibration signals, high-frequency measuring accelerometers were used for the measurements. A dataset of 60 RPM spindle speed with a 5.0 kN axial load was taken for both inner and outer race faults.

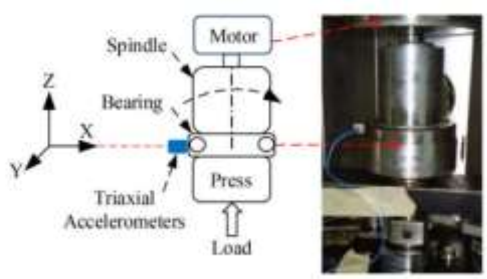

Figure 1. Test Rig used in this study[16].

2.2 Bearing faults and specifications

The two bearings categories considered in the experimental setup were healthy and faulty. The healthy bearings were simulated as control parameters for comparison. An intentionally created crack in the inner and outer races of the bearing was considered a fault. The fault created imitates a few common defects in the bearings, so it alters the vibration patterns significantly. The details of the ball bearing specifications used for the experiments are stated in Table 1.

Table 1. Ball bearing specifications and fault characteristic frequencies for bearing QJ212TVP.

Parameter	Value
Number of balls	15
Ball pass frequency inner race (BPFI)	15.87 mm
Ball pass frequency outer race (BPFO)	8.6427 Hz
Bearing pitch diameter	

2.3 Fault descriptions

In this study, various fault cases were introduced to the ball bearings to simulate real-world defects and evaluate the effectiveness of the proposed fault diagnosis method. The faults were introduced on both the inner and outer races of the bearings. Each fault was carefully designed and manufactured to ensure consistency and reliability in the experimental results. The test conditions for all cases involved a spindle operating at 60 RPM and an axial load of 5.0 kN. Below are the detailed descriptions of the fault cases:

2.3.1 Fault on inner race

(1) Fault 1: Dimensions, Width=1.0 mm, Depth=0.05 mm, Height=2.6 mm. Description: This fault represents a small defect on the inner race, characterized by a narrow and shallow groove. It simulates initial wear conditions that can occur in ball bearings under normal operational stress.

(2) Fault 2: Dimensions, Width=2.1 mm, Depth=0.20 mm, Height=5.0 mm. Description: This fault represents a moderate defect on the inner race, with increased width and depth compared to Fault 1. It simulates progressive wear that occurs as the bearing continues to operate under stress.

(3) Fault 3: Dimensions used are Width=3.8 mm, Depth=0.40 mm, Height=6.8 mm, Description: This fault represents a severe defect on the inner race, characterized by a wide and deep groove. It simulates advanced wear and potential crack formation that can lead to bearing failure if not detected early.

(4) Fault on Outer Race

(5) Fault 4: Dimensions Width=1.4 mm, Depth=0.05 mm, Height=2.6 mm, Description: This fault represents a small defect on the outer race, similar in size to Fault 1 but located on the outer race. It simulates initial wear conditions that can occur on the outer race due to operational stress.

(6) Fault 5: Dimensions Width=2.4 mm, Depth=0.20 mm, Height=5.0 mm, Description: This fault represents a moderate defect on the outer race, with increased width and depth compared to Fault 4. It simulates progressive wear that occurs as the bearing continues to operate under stress.

(7) Fault 6: Dimensions: Width=4.0 mm, Depth=0.40 mm, Height=6.8 mm, Description This fault represents a severe defect on the outer race, characterized by a wide and deep groove. It simulates advanced wear and potential crack formation that can lead to bearing failure if not detected early.

(8) Fault 7: Dimensions: Width=5.0 mm, Depth=0.40 mm, Height=6.8 mm, Description This fault represents a severe defect on the outer race, characterized by a wide and deep groove. It simulates advanced wear and potential crack formation that can lead to bearing failure if not detected early.

Below is an illustration of the typical faults introduced in the inner and outer races of the ball bearings:

Figure 2. Bearing used in this study[16].

These fault cases provide a comprehensive range of defect severities, allowing for a thorough evaluation of the fault diagnosis method's ability to detect and classify various stages of bearing wear and damage. The consistent test conditions of 60 RPM spindle speed and 5.0 kN axial load ensure that the results are reliable and comparable across different fault scenarios.

2.4 Data collection and feature extraction

The data collection process was meticulously planned and executed to ensure the reliability and accuracy of the vibration measurements. The experiments were conducted using the FALEX multi-specimen test bench[17], equipped with a comprehensive monitoring infrastructure, including force, speed, temperature, and vibration sensors[18]. The bearing test rig was fitted with three accelerometers (model PCB 356A32)[19] to measure triaxial vibrations along the x- y-, and z-axes at a sampling frequency of 25.6 kHz. For this study, only the x-axis measurements were used. Feature extraction is a critical step in the process of fault diagnosis as it involves transforming raw vibration data into a set of meaningful features that can be used to train machine learning models[20-22]. In this study, several statistical features were extracted from the time-domain vibration signals to capture the characteristics of the signals.

The following statistical features were extracted from the vibration data[16,23] (Table 2):

Table 2. Statistical features extraction formula

Features	Description
Mean (μ):	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$
Median	The median is the middle value of the ordered dataset.
Standard Deviation (σ)	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$
Minimum Value (Min)	Min=min $(x_1, x_2, \ldots, x_n)$
Maximum Value (Max)	Max=max$(x_1, x_2, \ldots, x_n)$
Range	Range=Max−Min
Mean Absolute Deviation (MAD):	$\text{MAD} = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i - \mu \rvert$
Skewness	$\text{Skewness} = \frac{N\sum_{i=1}^{N}(x_i-\mu)^3}{\sigma^3}$
Kurtosis	$\text{Kurtosis} = \frac{N\sum_{i=1}^{N}(x_i-\mu)^4}{\left[\sum_{i=1}^{N}(x_i-\mu)^2\right]^2}$
Dominant Frequency	The dominant frequency is the frequency component with the highest amplitude in the Fourier Transform of the signal.

where *xi* is a signal for *i*=1, 2, *N*, *N* is the number of data points.

2.4. Machine learning model and performance

The experiments were performed using the Random Forest classifier for fault diagnosis, which has proven to acceptably manage the effects of noise and high dimensionality in data[7,14]. Random Forest is an ensemble learning technique that constructs a set of decision trees during training and then aggregates the votes from different trees to output the class chosen by the majority of the individual trees[24]. It has been selected for its effectiveness in avoiding overfitting maltreatment common to individual decision trees, working well with a large dataset, and handling a mix of numerical and categorical features. The extracted statistical features from the vibration data consisted of mean, median, standard deviation, minimum value, maximum value, range, skewness, kurtosis, and dominant frequency. The Random Forest model's key hyperparameters, including the number of trees, maximum depth, and minimum samples per leaf, were optimized by grid search in which we trained the model on the available data and then a validation set was used to figure out the best combination of hyperparameters to be optimal for making predictions. The accuracy, precision, and recall with an F1-score realized to evaluate the Random Forest model were pointed out in the text, showing fully adequate performance for the classification of bearing conditions.

3. RESULTS AND DISCUSSION

3.1 Vibration signals for healthy and faulty states

In a more visual and demonstrative manner, raw vibration signals were processed to highlight the differences between healthy and faulty bearings[25,26]. Figure 3 depicts the vibration signals of a healthy bearing and a defective bearing with a fault on the inner ring (Fault 1). The vibration signal from the healthy bearing is characterized by relatively low amplitude with stable patterns, indicative of smooth operation. In contrast, the amplitude of the faulty bearing is much higher with variable patterns, reflecting the imposed fault. These visual differences corroborate the statistical feature analysis and the model's ability to distinguish between healthy and faulty states, aligning with previous studies on vibration signal analysis for fault detection.

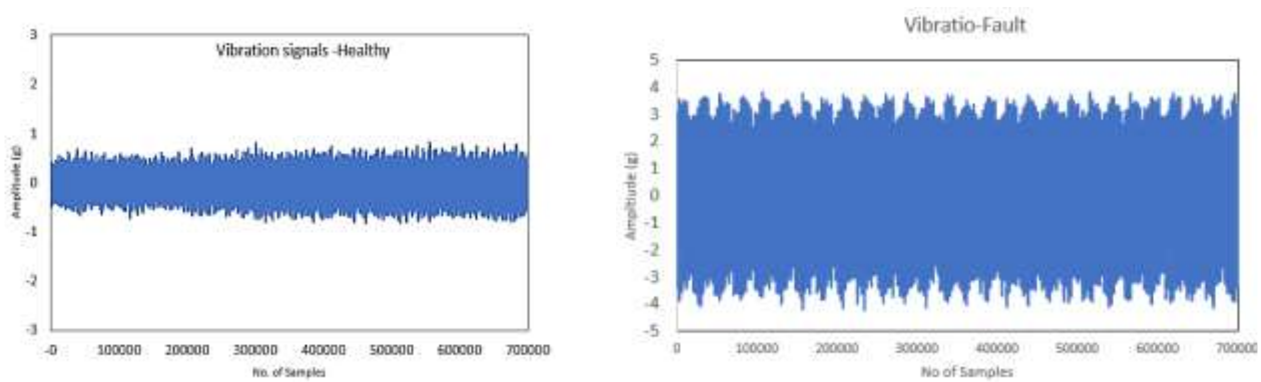

Figure 3. Vibration signals for healthy and fault status.

The vibration signal of the healthy bearing exhibits relatively low amplitude and consistent patterns, indicating smooth operation. In contrast, the faulty bearing's signal shows higher amplitude and irregular patterns, reflecting the presence of the fault. These visual differences corroborate the statistical feature analysis and the model's ability to distinguish between healthy and faulty states, supporting the findings of prior studies on vibration signal analysis for fault detection.

3.2 Feature analysis using descriptive statistics

Statistical features extracted from vibration signals provide valuable information about the nature of data from both healthy and faulty bearings. Examining these features reveals various fault conditions with distinct patterns and variability. Descriptive statistics represent the data's distribution and variability, crucial for effective fault diagnosis[16]. From Figure 4 can be observed the correlation matrix analysis was conducted to investigate the relationships among various features, aiding in selecting the most informative ones for the fault diagnosis model. Significant observations from the correlation matrix include:

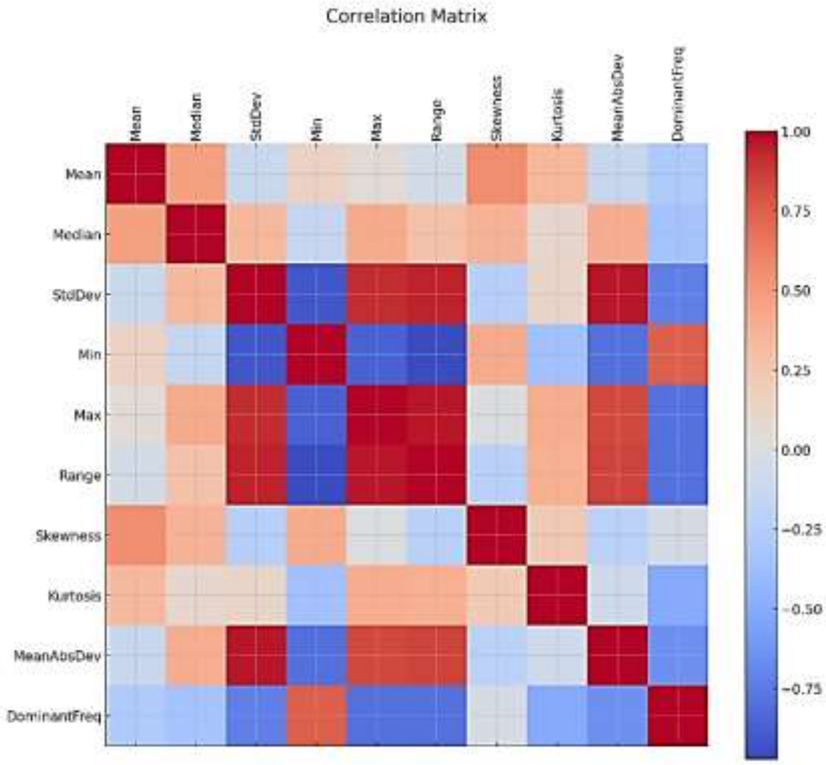

Figure 4. A correlation matrix[27].

- Mean and median features are highly correlated, indicating their shared capability to capture the central tendency of the vibration signal.
- Strong correlations were seen between minimum and maximum values and between the range and standard deviation, reflecting their measurement of related aspects of the signal's variability.
- Features such as skewness and kurtosis showed lower correlations with other features, suggesting their unique ability to capture distinct aspects of the signal's distribution.
- The dominant frequency feature also displayed a low correlation with other features, implying its distinct provision of information about the signal's frequency content.

These insights are crucial for selecting the most informative features for the fault diagnosis model, aligning with previous studies on feature selection in vibration analysis that underscore the importance of such analyses.

3.3 Model performance

The performance of the Random Forest model was evaluated using several metrics, including accuracy, precision, recall, and F1-score. The results are summarized in Table 3.

Table 3. Model performance metrics.

Metric	Accuracy CA	Precision	Recall	F1-Score
Value	90%	90.4%	90.42%	90.4%

The provided metrics show the classification of all the classes and different fault conditions by the model. This high level of accuracy, reinforced by appropriately balanced precision and recall scores, points to the expected excellent capacity of the model. It also fits very well with other studies conducted within a similar area, which uses machine learning in the same capacity for fault diagnosis.

4. CONFUSION MATRIX ANALYSIS

The confusion matrix in Figure 5 elicits detailed information about the classification performance of the model by exposing both the correctly and mistakenly detected instances for every class. The power of the model is evaluated through the confusion matrix, which defines the weaknesses of the model. It is obvious that the Random Forest model performed well and, hence, is suitable for diagnosing ball bearings.

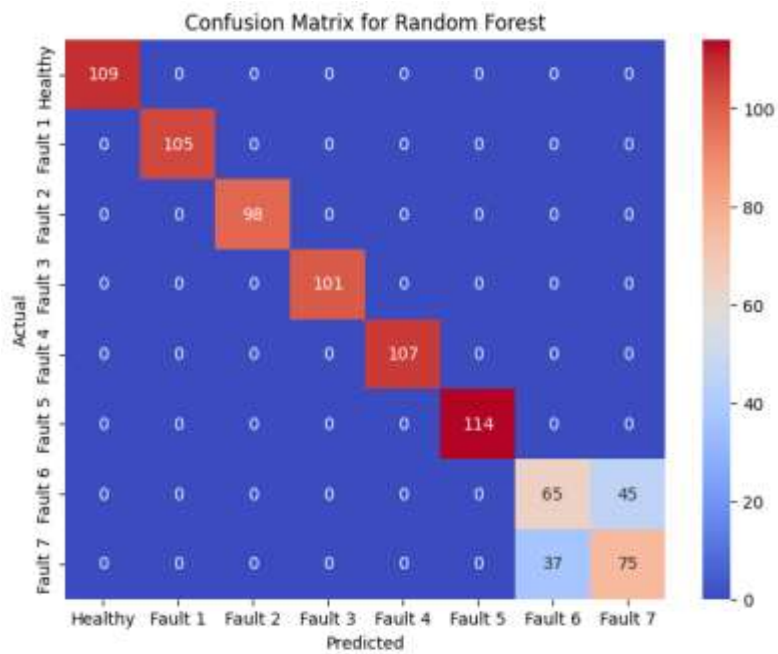

Figure 5. Confusion matrix of RF.

From the analysis of the correlation matrix, it is easy to identify the most informative features; the mean, median, skewness, and kurtosis are those most contributing to the precision of the model. Through detailed analysis using the confusion matrix, the model's performance in various fault conditions has been presented, and it also gives an idea about further refining areas of the model. This is congruent with previous research work, wherein it has been mentioned that feature selection and optimization of the model are very relevant to machine learning-based fault diagnosis[28,29].

5. CONCLUSIONS

This was an excellent way of presenting material in fault diagnosis involving vibration data and statistical feature extraction for ball bearings. The outstanding findings and contributions of this research are as follows:

(1) Datasets and fault cases: Any fault diagnosis contribution will require a relevant dataset. The authors, in this paper, use the dataset made available through the German Aerospace Center, DLR, meaningfully measuring healthy and faulty ball bearings enrolled in their work. Seven various fault cases have been generated regarding Inner Race and Outer Race defects while maintaining the experimental conditions: the same speed, 60 Rpm spindle speed, and 5.0 kN axial load.

(2) Feature extraction: A set of statistical features such as mean, median, standard deviation, minimum value, maximum value, range, skewness, kurtosis, mean absolute deviation, and dominant frequency were extracted from the vibration signals. The extracted features reflected the valuable information about the signal characteristics necessary for fault diagnosis effectively.

(3) Machine learning model: A Random Forest classifier was used in fault diagnosis; it is a very robust model in high-dimension data. Performance It is excellent, where accuracy equals 90.42%, precision weighted average to 90.43%, recall weighted average 90.42%, and F1score weighted average of 90.40%.

(4) Analysis and interpretation: From the study of the correlation matrix, some of the necessary features that led to the model's accuracy were identified; they include mean, median, skewness, and kurtosis. The confusion matrix brought out its ability to classify most fault conditions correctly, even though there were some misclassifications between similar fault types. They are taking into account that the results are consistent with previous machine learning-based fault diagnosis research.

(5) Challenges and future work: Despite promising results, several challenges remain. It is illustrated by the misclassification of some faults that the model and feature set should be refined further. Besides this, any noise and change in operational conditions may affect the model performance. In future studies, the model should be enhanced in that direction to differentiate the faults of similar types. More sophisticated features shall be extracted for better results, and techniques of noise reduction may be studied for more accurate fault detection. These systems can offer instant information about the health of ball bearings in real-time; hence, based on the proposed method, real-time fault diagnosis systems can be developed.

In this paper, the effectiveness of statistical features and Random Forest has been validated for diagnosing faults in ball bearings. The results obtained herein form a sound basis for further development and improvement of more advanced fault diagnosis to be real-time for enhancing the predictive maintenance and operation reliability of mechanical systems generally.

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