Bearing Fault Diagnosis using Decision Tree Machine Learning Model through Vibration Signal

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Abstract - Fault diagnosis of every rotating machine is very important to maintain its efficiency. Bearing is one of the vital elements in any rotating machinery. Therefore, condition monitoring and fault diagnosis of bearing is very essential. Vibration signal acquired from the bearings carries the information regarding the health of the bearings. The statistical parameters of the vibration signal are used as the inputs of the Decision Tree machine learning model to classify the faults in bearings. The results of this work show the effectiveness of the proposed model for fault diagnosis in bearings.

Keywords: Fault diagnosis, Bearing, Machine learning, Decision tree, Vibration signal.

I. INTRODUCTION

Every rotating machinery generates its own vibration signal in its healthy condition which is called as its vibration signature. But when the defect occurs in the bearings of any rotating machinery, then the vibration signature of that machinery gets changed. This change can be detected by measuring the vibration signal acquired from the bearings and the information can be extracted from the measured vibration signal. Then the machine learning model can be used to diagnose the faults in the bearings.

Various techniques have been followed in different researches for the fault diagnosis in bearings.

Many researchers show the use of vibration signal for health monitoring of bearings [1,2]. The vibration signal is also used as the measuring signal for health monitoring of wind turbines [3, 4]. In some past literatures it is found the application of wavelet transform and vibration signal to analyze and detect the defects [5-8]. The electrical current signature can also be used in the fault diagnosis of rotating machinery [9,10]. Statistical parameters of the vibration signal can be used for the fault detection in bearings [11]. The morlet wavelet can also be used for feature extraction from the measuring signal for machine fault detection [12]. Frequency analysis can also be used for the fault diagnosis of bearings. Kankar, P. K et al. explains the use of machine learning techniques for the fault diagnosis of ball bearings.

The proposed work shows the use of machine learning model for the fault diagnosis of bearings through vibration signal. The statistical parameters are extracted from the vibration signal acquired from the experimental setup. These statistical parameters are used as the inputs to the machine learning model to classify the faults in the bearings. The Decision Tree machine learning model is used in this work. Though the extracted statistical parameters detect the presence of defects in the bearings, but the machine learning model (Decision Tree) diagnose the faults in the bearings more precisely.

1.1 Time Domain Study

In time domain analysis the statistical features are computed from the vibration signatures. Then the statistical parameters of the vibration signal acquired from the healthy bearing are compared with the statistical parameters of the vibration signature acquired from the defective bearings. By comparing these statistical features, the faults in the bearings can be identified. The statistical parameters used for the time domain analysis are RMS, skewness, mean, peak value, crest factor, kurtosis, standard deviation, clearance factor, impulse factor and shape factor.

1.2 Decision Tree Machine Learning Technique

Decision Tree is a supervised learning technique that can be used for both classification and regression problems, but mostly it is preferred for solving classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.

In a Decision Tree, there are two nodes, which are the Decision Node and Leaf Node. Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.

The decisions or the test are performed on the basis of features of the given dataset. It is a graphical representation for getting all the possible solutions to a problem/decision based on given conditions. It is called a decision tree because, similar to a tree, it starts with the root node, which expands on further branches and constructs a tree-like structure. A decision tree simply asks a question, and based on the answer (Yes/No), it further split the tree into subtrees. Figure 1 shows the concept of Decision Tree.

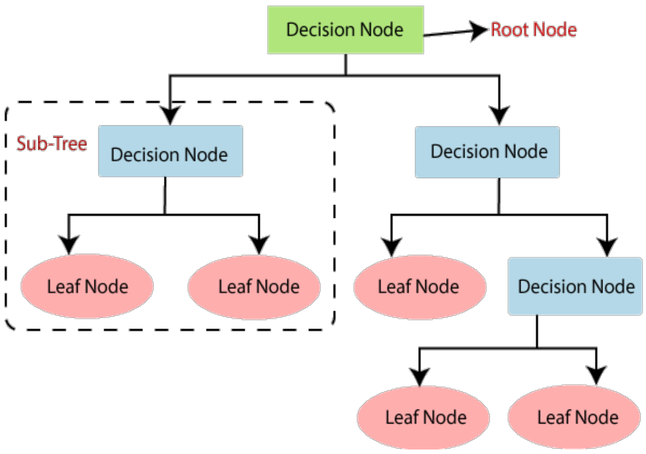

Figure 1. Decision Tree algorithm basic concept

II. METHODOLOGY

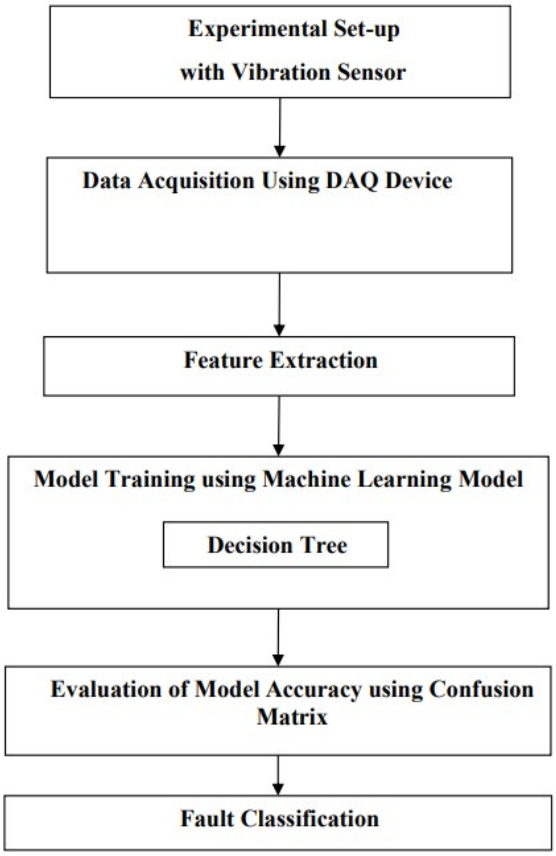

Figure 2. Flow graph of proposed work

The flow graph of the proposed work is shown in figure2.The experimental system is developed to acquire vibration signals from the healthy and defective bearings. The DAQ device is used to acquire the vibration signal. Then different statistical parameters are extracted from the measured vibration signal. These statistical parameters are used as the inputs to the machine learning model to classify the faults. The confusion matrix is used to calculate the model accuracy in fault classification.

III. EXPERIMENTAL PROCEDURE

An experimental setup has been made to implement the proposed work. The schematic of the experimental setup is shown in figure 3 and the real experimental setup is shown in figure 4.

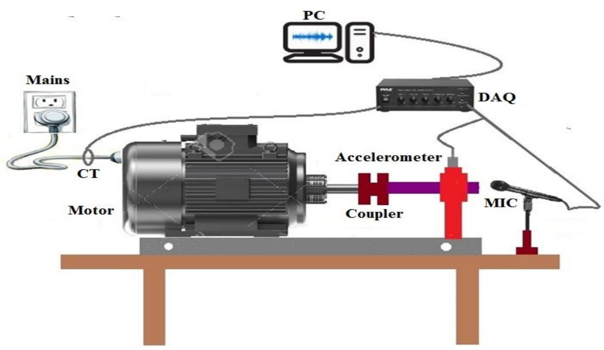

Figure 3. Schematic of the experimental setup

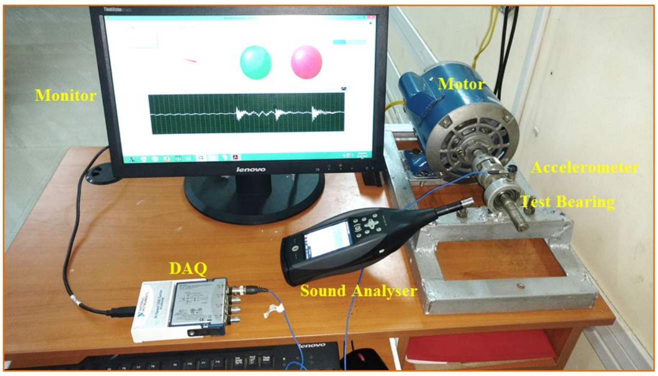

Figure 4. Experimental setup

The experimental setup consists of a single-phase induction motor. At zero load, the speed of the motor is 1000. The bearing under test is mounted on the rolling shaft of the motor. Three number of bearings are used for the experiment. One healthy bearing and two defective bearings. This is shown in figure 5 and figure 6.

The accelerometer (PCB 325c-03 Accelerometer) is used to sense the vibration. To acquire the vibration data a 4-channel data acquisition system is used. For this purpose, the NI 9234 DAQ card along with a PC with LabVIEW software is used. In the experiment two deferent types of defected bearings are used named as type-I and type-II defect bearing. The data acquisition is done in three different stages. In first stage the healthy bearing is mounted and the corresponding data is acquired. Then in second stage the type-I defect bearing is mounted and the data is acquired. In third stage, the type-II defect bearing is mounted and the corresponding data is acquired. The vibration signal acquired from the healthy, type-I defect and type-II defect are shown in figure 7, figure 8 and figure 9 respectively.


Figure 5. The healthy bearing

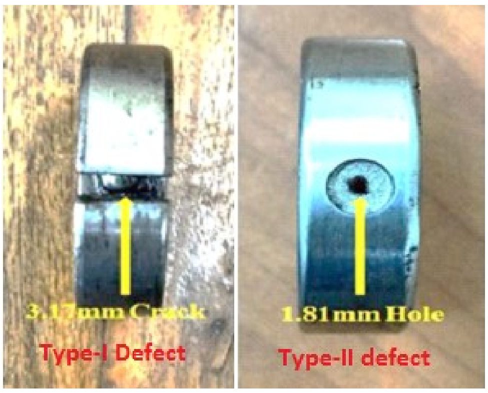

Figure 6. The Type-I and Type-II defect bearing

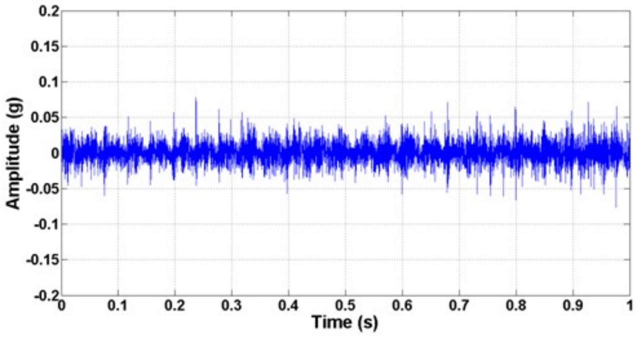

Figure 7. Vibration signal from Healthy bearing

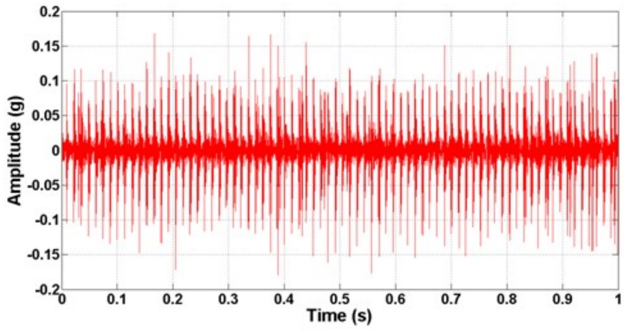

Figure 8. Vibration signal from type-I defect bearing

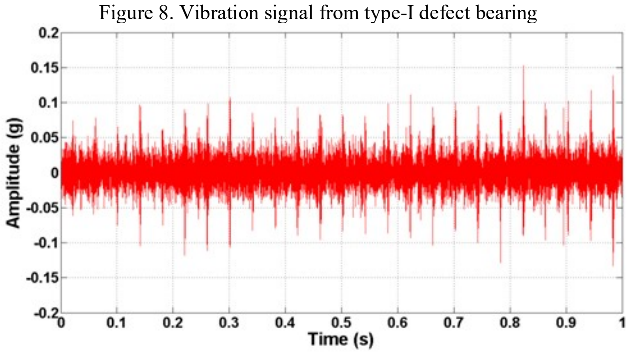

Figure 9. Vibration signal from type-II defect bearing

IV. RESULTS AND DISCUSSION

Sl. No	**Time Domain Parameters**	**Healthy Bearing**	**Type-I Defect Bearing**	**Type-II Defect Bearing**
1	Root Mean Square (RMS)	0.0234	0.0361	0.0304
2	Mean	0.5235	0.1234	0.1001
3	Peak Value	0.0776	0.1434	0.1410
4	Crest Factor	4.2240	5.1250	6.4403
5	Skewness	-0.0012	-0.1250	0.0150

6	Kurtosis	2.7532	8.3250	6.3250
7	Variance	0.0240	0.2459	0.1540
8	Standard Deviation	0.0240	0.0451	0.0350

Table1. Time domain parameter comparison

The result is discussed under two sections. Fault detection using time-domain analysis and fault classification using machine learning model.

Time Domain Analysis:
The time domain analysis is done to detect the faults in the bearings. The statistical parameters such as kurtosis, skewness, crest factor, mean, RMS, peak value, variance, standard deviation is computed and is tabulated in table 1. From the tabulation it can be clearly observed that the statistical parameters are changed when the bearing is in the defective conditions in comparison to the healthy condition.

Machine Learning Model:
Though time domain analysis can detect the faults in the bearings, but it can't diagnose the faults precisely. Therefore, the machine learning model is used for the classification of the faults. The confusion matrix and the accuracy opted using the Decision Tree machine learning model is shown in figure 10. The percentage model accuracy obtained from this confusion matrix is 82.

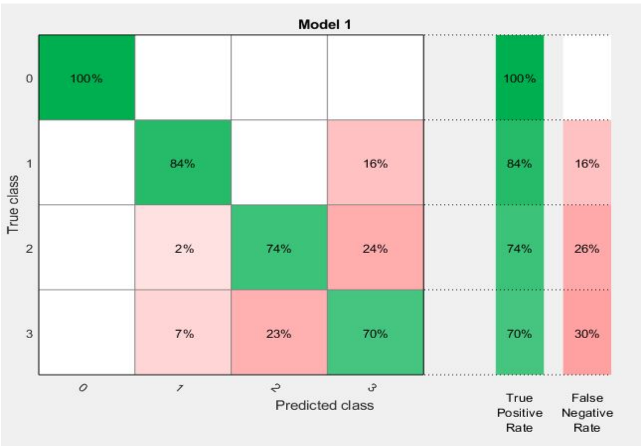

Figure 10. Accuracy opted using Decision Tree classifier model

V. CONCLUSION

The proposed experimental work shows the application of statistical analysis and Decision Tree machine learning model for the fault diagnosis in the bearings of the rotating machinery. The statistical analysis though suitable to identify the defect but the Decision Tree machine learning model is more informative and classify the faults. The model accuracy can be improved by using the filtered vibration signal. The other machine learning models may be tested to get better result of fault classification.

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