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Motor Bearings Fault Classification using CatBoost Classifier

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Abstract— Induction motors are used in all industries and are the major element of energy consumption. Faults in motor degrade the motor efficiency and result in more energy consumption. Bearing faults are reported to be the major reason for the motor breakdown and a lot of papers have been reported to focus on bearing fault diagnostics. However, low classification accuracy is the main hurdle in adopting the available fault classification algorithms. This paper has presented a novel classification algorithm using the Catboost classifier and time-domain features. The developed algorithm was tested on the laboratory test setup. The fault classification accuracy of 100 % was achieved through the proposed method.

Keywords: Condition Monitoring, Time Domain Features, Fault Classification, CatBoost Classifier.

1. Introduction

Induction motors are used in the industry for the conversion of electrical energy to rotational mechanical energy. They are the key elements of the industry and consume 45 % of the global energy [1-3]. The efficiency of the motors is reduced if faults appear in the motor. The faulty motors consume more energy as compared to healthy motors. Bearings are installed in the motor to assist the rotation and 41 % of the motor faults are due to bearing problems. Thus, a suitable condition monitoring system can assist to protect the motor from sudden breakdowns and ensuring safe operations [5-9].

Vibration analysis is a very famous method for the fault diagnostics of the bearings. It requires an accelerometer for vibration measurement and measured data is fed to the software for further analysis. The time-domain data require experts for the analysis and interpretation to differentiate between healthy and faulty conditions. Thus, an automatic classification system is required for quick and reliable decision-making. A lot of research has been conducted in the past to use machine learning and deep learning tools for fault diagnostics and fault classification. However, low classification accuracies are the real challenge that requires attention [10-20].

This issue has been addressed in this study where the ensemble learning tool known as Catboost classifier has been developed to analyze the statistical features of the time domain data. The four statistical features known as variance, standard deviation, skewness and kurtosis were used for the classification of bearing health as healthy bearing (HB), inner race (IR) faults and ball defects (BD). The statistical parameters are used to evaluate the time domain data. The parameters such as Variance, Standard Deviation, Skewness and Kurtosis are calculated for the healthy bearing and faulty bearing. The variation in the values of Variance, Standard Deviation, Skewness and Kurtosis indicate the presence of the fault in the bearing. The details of the features have been given in the following section:

Variance (VAR): Variance indirectly measures the data distribution from the mean of the segment. This is the second central moment of distribution and calculated using equations (1) and (2) [18-20].

$$VAR = \frac{1}{X}\sum_{j=1}^{X} |Zj - \sigma|^2 \quad (1)$$

Where

$$\sigma = \frac{1}{X}\sum_{j=1}^{X} Zj \quad (2)$$

Standard Deviation (STD): Standard deviation is the positive square root of the variance to measure the variation of data from equation (3) [19].

$$\text{STD} = \sqrt{\frac{1}{X}\sum_{j=1}^{X} |Zj - \sigma|^2} \quad (3)$$

Skewness (SKW): Skewness is the third moment of distribution to measure the asymmetry of the probability distribution about its mean from equation (4) [19].

$$\text{SKW} = \frac{\frac{1}{X}\sum_{j=1}^{X} |Zj-\sigma|^3}{\left(\sqrt{\frac{1}{X}\sum_{j=1}^{X} |Zj-\sigma|^2}\right)^3} \quad (4)$$

Kurtosis (KURT): Kurtosis is the scaled form of the fourth moment to find tailness in the probability distribution curve and is represented using equation (5) [19].

$$\text{KURT} = \frac{\frac{1}{X}\sum_{j=1}^{X} |Zj-\sigma|^4}{\left(\frac{1}{X}\sum_{j=1}^{X} |Zj-\sigma|^2\right)^2} \quad (5)$$

The rest of the paper has been organized as follows: the experiments arrangement has been illustrated in section 2. The results and discussions have been described in section 3 and section 4 presents the conclusion.

2. Experiment Design

The experiments were performed on the dedicated test setup for condition monitoring of motors and pumps. The test setup consists of a centrifugal pump, induction motor, water storage tank, vibration sensor, stator current sensors, LabVIEW, Matlab and data acquisition interface. The faulty bearings and data acquisition card have been shown in Figure 1. The test setup has been shown in Figure 2. Three case scenarios of the motor bearing are considered in this paper which are Healthy Bearing (HB), Inner Race Defect (IRD) (size 3 mm hole) and Ball Defect (BD). The motor operating speed was 1440 rpm. The bearings under consideration were installed on the drive-end side. The sampling rate was 10 K samples per second. The data was saved as M-files and was plotted using MatLab and analyzed using Python, Spyder (5.1.5). The statistical features (standard deviation, variance, skewness, kurtosis) were extracted from the time domain data and were used in the fault classification algorithm. The flow chart of the developed classification system has been shown in Figure 3.

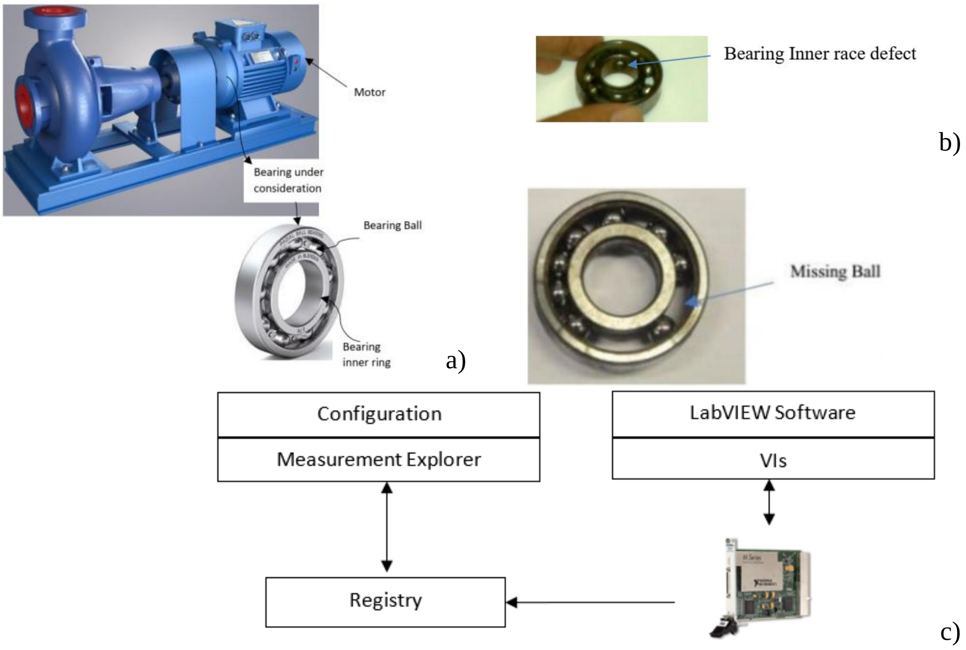

Fig. 1. The components of the test rig (a) bearings assembly (b) faulty bearings (c) data acquisition card configuration

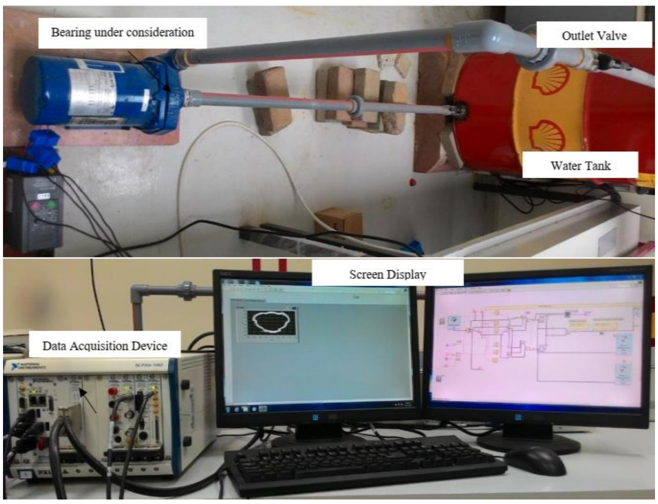

Fig. 2. The laboratory test setup

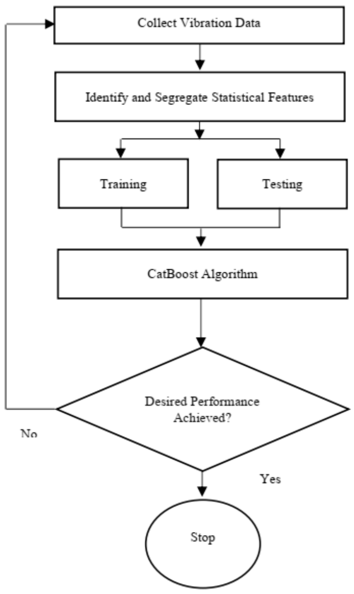

Fig. 3. The flow chart of the proposed system

3. Results and Discussions

The vibration data was collected and a sample plot has been shown in Figure 4. The statistical features (standard deviation, variance, skewness, kurtosis) were extracted from the time domain data and were used in the Catboost algorithm. The parameters of the algorithm are learning_rate=0.001, depth=10, loss_function='MultiClass'. The values of the extracted features are given in Table I. In machine learning, the confusion matrix is used to indicate the performance of the algorithm. It indicates the error performance by indicating that how many samples were misclassified by the algorithm. The confusion matrix has been shown in Figure 5. The confusion matrix indicates that all classes have been correctly classified with 100 % classification accuracy which indicates the strength of the catboost classifier for condition monitoring applications.

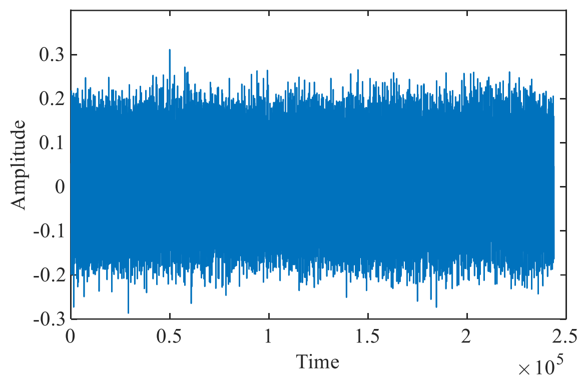

Fig. 4. The sample data

Table I. Extracted values of the features

Sr. No	Feature Name	Feature Value for HB	Feature Value for BD	Feature Value for IR
1.	Standard Deviation	0.732009	0.789520	0.764368
2.	Variance	1.24979	1.308426	1.297852
3.	Skewness	0.0255599	0.0296752	0.02719852
4.	Kurtosis	-0.224665	-0.156523	-0.187625

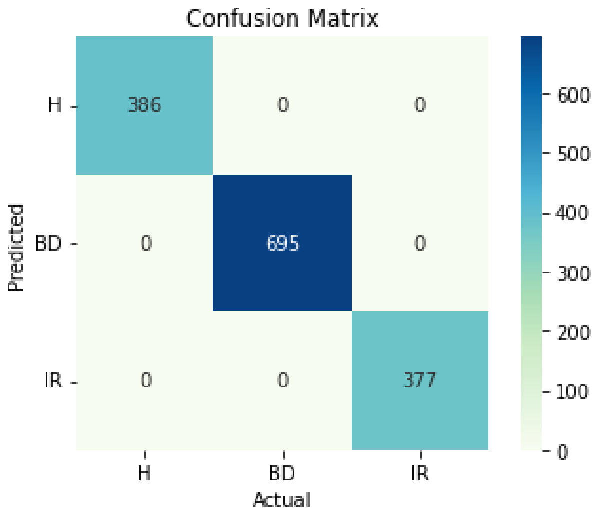

Fig. 5. The confusion matrix

4. Conclusions

This paper has focused on developing a bearing fault classification system using a Catboost classifier. The vibration data has been collected and statistical features have been segregated. The three situations of the bearing labeled as healthy bearing, inner race faults and ball defects have been studied. The Catboost classifier was programmed in Python, Spyder library. The experimental results indicate that the classifier was able to classify the three classes with 100 % accuracy. The scope of this work could be further extended in the future to include more fault types such as gear faults, impeller faults and shaft misalignments to develop a complete condition monitoring package for the industry.

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