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Machine Bearing Fault Diagnosis System using Tri-Axial Accelerometer

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Abstract—**Bearing fault is the leading cause of the entire rotating machinery system failure. The fault diagnosis of machinery consists of features extraction and fault classification. The main purpose of this research is to develop a platform with less complexity and more accuracy for the early fault detection in machines and classification of faults. This study also focuses to present efficient, low-cost, and more reliable methods for fault detection and diagnosis. The vibrations data was collected from the rotating machinery (motor) with the AX-3DS wireless Tri-axial accelerometer. We obtained dataset vibrational signals of three states of the machines, namely, Normal, inner race bearing fault, and outer race bearing fault. For preprocessing and segmentation purposes we employed Empirical mode decomposition. Only two features namely Skewness (SK) and Root mean square (RMS) were extracted from three axes and fed to the Support vector machine (SVM) classifier. The proposed method yields an average accuracy of 99.8% on the dataset gathered. Such a compact, less costly, and the more accurate system will help industries for early fault diagnosis of machinery.**

Keywords—Fault diagnosis, empirical mode decomposition, Support vector machine, feature extraction, accelerometer sensor.

I. INTRODUCTION

This In industries, rotating machinery is the vital component having wide applications in modern society. Nowadays, with the rapid development in science and technology machine structures are becoming more complex, and various mechanical components are closely connected. For the mechanical equipment maintenance, rotating machinery continuous monitoring and fault diagnosis play an important role in this field. Due to some of the factors such as human fault, heat generation, looseness, faults may temporarily develop in the system. Hence, to avoid a large breakdown of the failure of rotating machinery it is important to identify faults on an early basis and diagnose them before they become critical and the failure of one component may cause damage to the whole equipment. For smooth machinery operation, the main vital component is the bearing which is usually forced by heavy loads.

In machinery bearing, fault diagnosis sensor signal acquisition is the primary stage of real-time fault diagnosis. Vibration analysis has many applications in the machine fault diagnosis[1]. In addition to that, there are other techniques visual inspection and acoustic signals were also used but these techniques did not determine the life of bearing. During the operation of any mechanical equipment, vibration signals were collected by different sensors then the vibration analysis techniques were implemented on a dataset for the fault diagnosis. Feature extraction, feature selection, and also fault classification are the two other main steps vital for the machine faults diagnosis [2]. The main target of this research is that to build an efficient system which is widely used for the initial diagnosis of machinery, has maximum accuracy. In addition to that, this system has many advantages as it includes low manufacturing cost, high accuracy means more precise, early faults are identified and monitored which saves whole system failure. Time-frequency examination approaches are used to contract with vibration signals gathered from a tri-axial accelerometer sensor and these methods are widely used for machine fault diagnosis [3].

II. LITERATURE REVIEW

Different techniques and methods were proposed by numerous authors on the diagnosis of faults in rotating machinery. The power spectral density analysis technique was proposed in [1] to detect multiple faults diagnosis in rolling bearings of rotating machinery. Types of faults in bearing include: inner race, fault outer race, ball fault, and combined faults have been analyzed by data taken from Spectra Quest's Machinery Fault Simulator through the accelerometer. In [2] the fault diagnosis of gear wear, misalignment of bearing, failure of an outer and inner ring of bearing in rotating machinery have been studied. Sample entropy and the multi-scale entropy were the techniques proposed. Multi-scale entropy classifies faults more effectively. In [3] the techniques for the bearing faults and gearboxes include tooth crack, wear, eccentric gear faults diagnosis in rotating machinery were presented. For both

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feature extraction and fault diagnosis, a Deep neural network (DNN) in this paper was proffered. In addition to that, the backpropagation neural network empirical mode decomposition (EMD), support vector machine (SVM), fast Fourier transforms techniques were studied. Compared with various classifiers, DNN has a maximum accuracy of 96.333%. In [4] authors proposed a Deep learning-based method named deep recurrent neural network and SoftMax classifier for fault identification of bearings in rotating machinery. It has been seen that the proposed method has maximum testing accuracy of 97.25%. In respectively, [5] bearing and rotor imbalance faults diagnosis in the field of rotating machinery were presented. A sample segmentation method, data augmentation method, and scaled conjugate gradient algorithm were the three methods proposed in this study. The maximum accuracy achieved in bearing faults diagnosis was 99.9% and in the rotor case, the max accuracy achieved was 99.6%. Conditioned Based Maintenance technique was presented in [6] for the common faults such as unbalanced and misalignment diagnosis in rotating machinery. For the fault classification using vibration analysis comparatively easy method for fault, classification was found. It includes acceleration amplitude and local maximum acceleration amplitude and k-nearest neighbors (KNN) was implemented for classification. The maximum accuracy at KNN classifier achieved in this research was 96%. In [7] adaptive weighted multi-scale convolutional neural network method was proposed for the bearing faults diagnosis in rotating machinery. In this paper, to check the success of the proposed models' convolutional neural network (CNN) and other multiscale CNN, both the train and bearing dataset given by Case Western Reserve University are being compared. The maximum accuracy achieved was 99.78%. In [8] vibration analysis techniques based on Fast Fourier transform and inverse fast Fourier transforms were used for the bearing faults diagnosis in rotating machinery. local temporal self-similarities is a technique used for the feature extraction in vibration analysis presented in [9]. The bag-of-words scheme is then used for the classification of rolling bearing faults in rotating machinery from these features. Both in K-NNC and SVM the identification rate is higher when the codebook size K is at a higher value, it can be 99 % and, in some cases, up to 100%. In [10] authors introduce bearing faults diagnosis in wind turbine. New methods being applied named: Integral Extension load mean decomposition, least squares support vector and Multiscale Entropy for the machine fault diagnosis. The mean maximum accuracy achieved at this proposed method is 99.2% as compared with local mean decomposition and SVM. In [11] SVM and incremental support vector machine both methods were formally introduced by researchers in this paper. In addition to that simulations were put through the Intelligent Maintenance System for the vibrations dataset of bearing faults diagnosis in rotating machinery. For both Inner race (IR) and outer race (OR) fault the accuracy achieved is maximum at ISVM which is 94.49% for IR and 98.73 for OR. Bearing faults diagnosis in the motor was discussed in [12]. Two very unique methods Wavelet auto-encoder and extreme learning machine were put forward for fault detection and identification purpose. Average max accuracy in this case was 95.20%. In [13] rotatory machinery faults diagnosis in gearbox and bearing were presented. For the faults identification purpose the techniques DNN, adaptive batch normalization, and stacked autoencoders were studied. In mean (%) the maximum accuracy was 96.33% in the method proposed. In [14] Different types of faults induction motor, gearbox, and bearing such as Normal motor Stator winding defect Unbalanced rotor Defective bearing Broken bar Bowed rotor were studied. Generative Adversarial Networks, Auxiliary classifier generative adversarial networks, Model evaluation were the techniques proposed for the fault's diagnosis. Classification accuracy range from 99.33-100% using real and generated dataset. In induction motor gearbox, Broken tooth, Crack, Normal were the faults proposed for the diagnosis purpose in [15]. Frequency-modulated empirical mode decomposition, energy entropy and SVM were the techniques that were used by researchers in this paper for diagnosis purpose. Maximum accuracy achieved was 90%. In [16] the authors discussed that the tool of mechanical and electrical faults in induction motor was based on multiclass support vector machine (MSVM) technique. Total ten different faults including five mechanical, four electrical and one normal were studied and diagnosed by using MSVM. For classification purpose vibrations max accuracy was 97.48% at high load, Current max accuracy was with no load that is 77.84% and Vibrations and Current both Accuracy was 93.55% at high load. In [17] the authors measured and analyzed the faults of motor bearing and a gearbox in rotating machinery. The method least squares recursive projection twin support vector machine and scattering transform were used for the detection and diagnosis of faults. Effectiveness of this method had been cleared by comparing this proposed method with other public approaches counting proximal support vector machine, the standard support vector machine and multi-scale theory, In [18] Zhong introduces a new method for the detection and diagnosis of automotive engine faults in rotating machinery. in this research multiple techniques were studied: ensemble empirical mode decomposition in the first stage for the decomposition of signal then probabilistic committee machine, in which multiple pairwise-coupled sparse Bayesian extreme learning machines are on separate basis were trained. In classification the maximum accuracy of 92.62% for single-faults, 85.73% for simultaneous faults, and 88.74% overall faults at PCM. Whitened Cross-correlation Spectrum (WCCS) is a techniques used in [19] for the bearing fault diagnosis in rotating machinery . Compared to other methods it can be seen that the WCCS provides more accurately fault detection without bandpass-filtering. In [20] the method described name one-dimensional convolutional neural network to analyze the gearbox faults diagnosis in rotating machinery. As this proposed method give high accuracy when compared with other three methods it proved its effectiveness. This method also proved its effectiveness when it achieved high accuracy at Prognostics and Health Management 2009 gearbox challenge data. Maximum accuracy achieved by using this proposed method was 99%. In [21] the authors presented new method based on infrared thermography for rotating machinery through which the bearing fault diagnosis were studied. In addition to that two methods for the extraction of features namely bag-of-visual-word, and CNN, were also discussed. At transient state the maximum accuracy was 99.8% and at steady state the maximum accuracy was 98.9% in this proposed method.

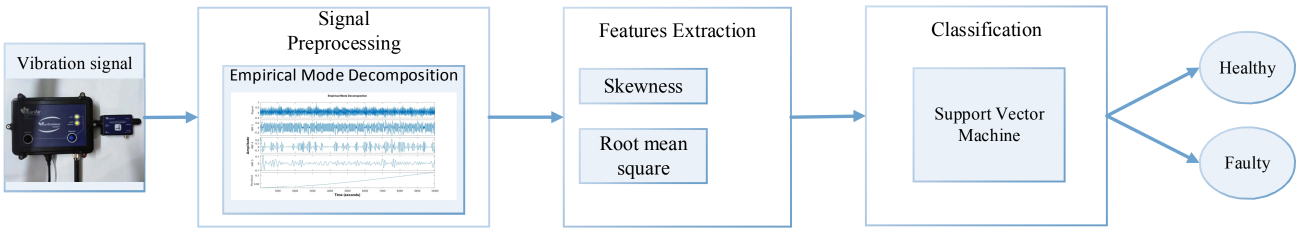

Fig.1. System block diagram

III. Methods and Materials

The proposed methodology for the identification, detection, and classification of bearing faults in rotating machinery is shown in figure 1. The first step is to acquire data of healthy and faulty bearing in the form of vibrations from a sensor. The next step is to apply the preprocessing and segmentation techniques on the raw signal acquired to denoise and examined the signal more effectively. After that, the features are extracted and finally classification is done to classify the data into healthy and faulty rotating machinery.

A. Data acquisition

In this article, vibrational data was acquired from Bean Device® AX-3DS wireless Tri-axial accelerometer as shown in Fig.2 developed by Bean Air corporation. The Bean Air device consists of Bean Gateway Outdoor and Indoor versions. Bean Gateway Outdoor is connected to the computer through an ethernet cable and Bean Scape software is used to communicate it with a wireless indoor version. The sensor is very sensitive and we gathered data at a sampling frequency of 1000 Hz (fs=1000Hz). Our main focus here in this research is the diagnosis of bearing consists of the outer race and inner race faults in rotating machinery. The rotating machinery used for this research is the quarter horsepower motor shown in Fig.3, which runs at a speed of 600 rotation per minute (RPM). The vibrational signals were gathered from the sensor mounted on the upper side of the motor. Table I shows the summary of the acquired data in detail. Fig. 4 and 5 show raw healthy and unhealthy versions of machine vibrations (along x-axis) respectively.

Fig.2.Tri-axial accelerometer

Fig. 3. Motor used in data acquisition process

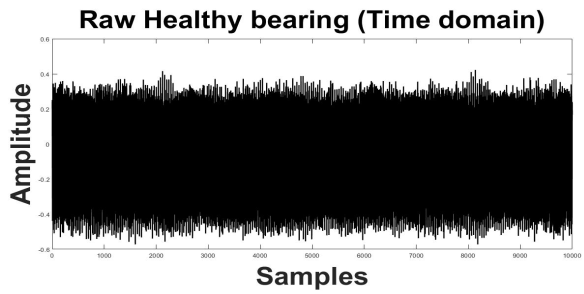

Fig.4. Raw Healthy Bearing X-Axis

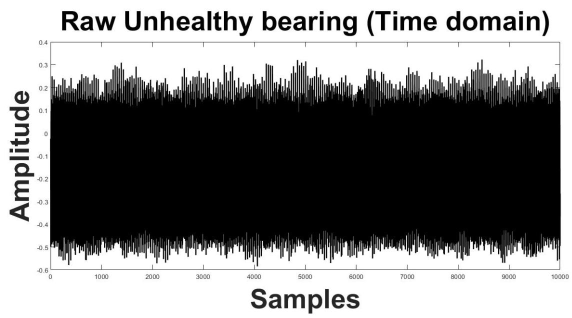

Fig. 5. Raw Unhealthy Bearing X-Axis

B. Preprocessing and segmentation

The vibrational data signal acquired from the accelerometer sensor is yet raw and contains a lot of noise and some other artifacts. Preprocessing and segmentation techniques must be applied to remove noise and other artifacts which is necessary to extract the region of interest accurately. For this purpose, Empirical mode decomposition (EMD) [22-25] is the technique used for noise removal, to examined signals more accurately and by using this we can

TABLE I. SUMMARY OF DATA

Type	Time (seconds)	Samples
Healthy	10	1155
Faulty	10	2310

easily extract our region of interest. EMD is a method of decomposing signals which are often non-linear and non-stationary into independent signal components known as Intrinsic mode functions (IMFs) without leaving the time domain.

The first IMF extracted contains the highest frequency and a lot of noise as compared with other IMFs. The last IMF has the lowest frequency signs and finally residual contains the trend of the signal. Fig. 6 and 7 show the EMD of healthy and faulty signals containing 10 IMFs. By examining Fig.4 and 5 it is clear that the IMF 3 4 5 contains the most discriminative behavior in contrast with other IMFs for healthy and faulty bearing. So, IMFs 3, 4, and 5 are designated as the area of notice and the remaining ones being removed. The segmented signals of the healthy and faulty bearing are presented in Fig. 8 and 9 individually.

C. Features extraction

The next step is the extraction of features containing distinct patterns. The main aim is to enhance the efficiency of the classifier, for this, it is necessary to find out the most compacted and discriminative set of features that can best distinguish between the healthy and faulty bearing using vibration signals. In this research, only two types of features are hauled out from the vibration signals which are: Skewness (SK)and Root mean square (RMS) for an assortment of vibration signals waveforms.

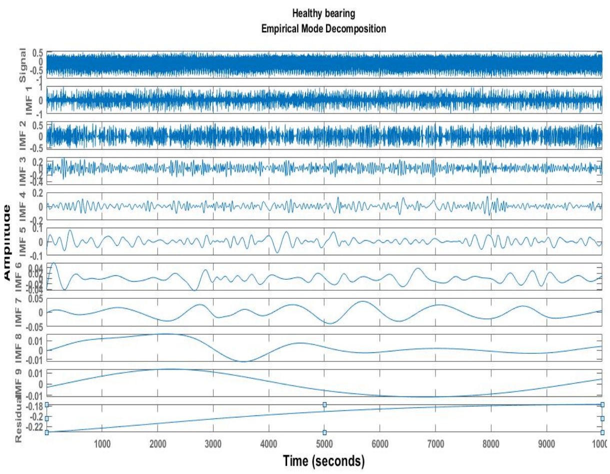

Fig. 6. IMFs (1-9) of Healthy bearing

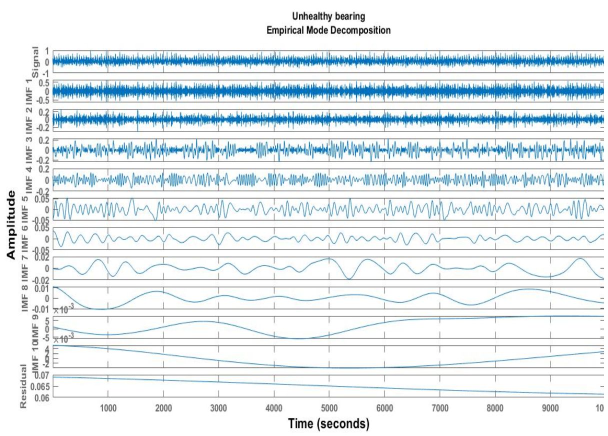

Fig. 7. IMFs (1-10) of Unhealthy bearing

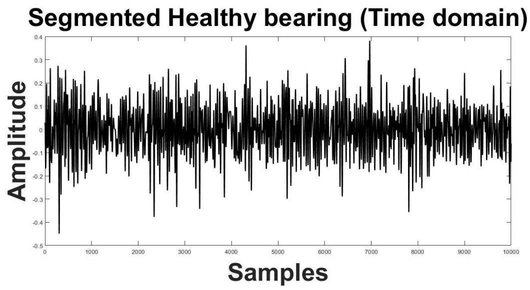

Fig.8. Segmented Healthy Bearing X-Axis

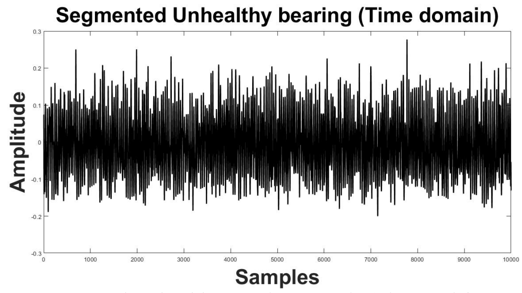

Fig. 9. Segmented Unhealthy Bearing X-Axis (Time and frequency domain)

D. Classification

The classification method we have chosen in this article is the support vector machine (SVM) [26-30] to categorize the acquired vibration signals: Healthy and faulty bearing. SVM is a supervised machine learning algorithm mostly used for classification purposes [31-33].

IV. Results and Discussion

In this research article, the signal processing context for the recognition of Bearing faults is presented. Raw signal gathered from the sensor is preprocessed and segmented using the EMD algorithm. Furthermore, features study is carried out to find out the best distinctive features containing distinguishing statistics. For this purpose, mean (m), standard deviation (STD), Root sum of squares (RSSL), Band power (BP), Skewness (SK), Root mean square (RMS), Crest factor (CF), Log Energy (LE), Occupied bandwidth (OBW) are applied as features. The clear analysis of these given features using SVM-MG (Medium Gaussian SVM) is shown in Table II. From the table, it is clearly shown that only by using two features namely Skewness (SK) and Root mean square (RMS), the system yields maximum accuracy of 99.8%. Thus, based on this and examining other features only these two features (SK and RMS) are designated for feature extraction.

Fig.8 presents performance analysis of different nine classifiers namely Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM (SVM-MG), Coarse Gaussian SVM, Fine KNN, Coarse KNN, Cosine KNN, Cubic KNN, and Weighted KNN, consuming the nominated features. Through the experiment, it is clear that the SVM-MG is the top performer classifier in this with an accuracy of 99.8% and error of just 0.2% respectively. 10-fold validation is used to evaluate the functioning of a classifier. A number of observations using this presented research are exposed in Fig.12. Only 2 out of 1155 healthy records are misclassified and 6 out of 2310 unhealthy(faulty) vibration signals are detected with a healthy label by SVM-

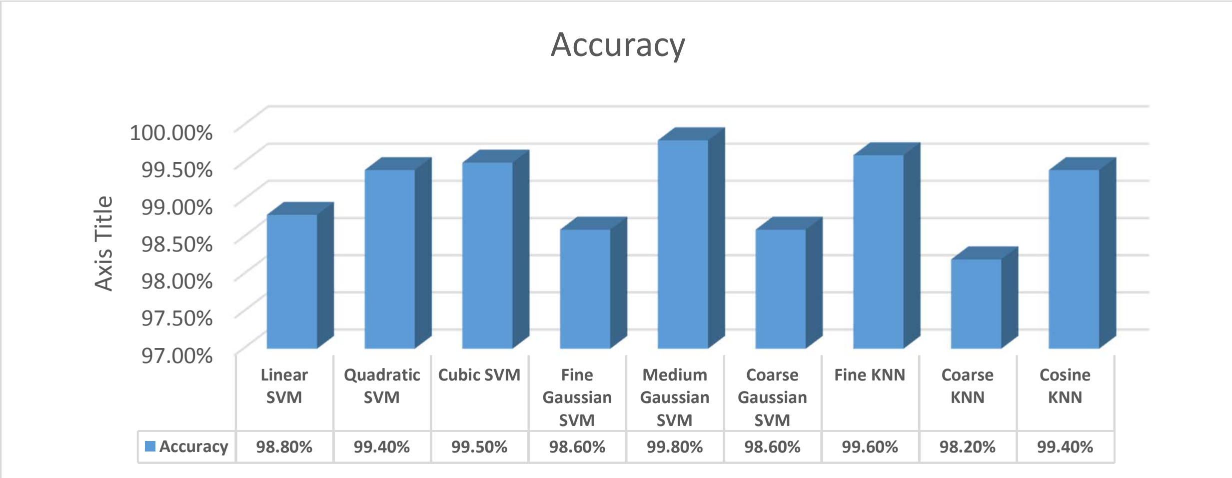

Fig.10. Performance comparison with different classifiers

TABLE II. SUMMARY OF SVM-MEDIUM GAUSSIAN CLASSIFIER ACCURACY ON DIFFERENT GROUPING OF FEATURES

M	STD	RSSL	BP	SK	RMS	CF	OBW	LE	Accuracy
×		×	×			×	×		**99.1%**
		×	×	×					**99.0%**
×	×		×		×		×		**99.7%**
	×	×				×		×	**99.7%**
			×	×				×	**98.9%**
				×	×				**99.8%**
×	×	×	×	×	×	×	×	×	**99.2%**

MG. In assessment with other prevailing studies, our given method customs less features and yield maximum accuracy of 99.8% respectively.

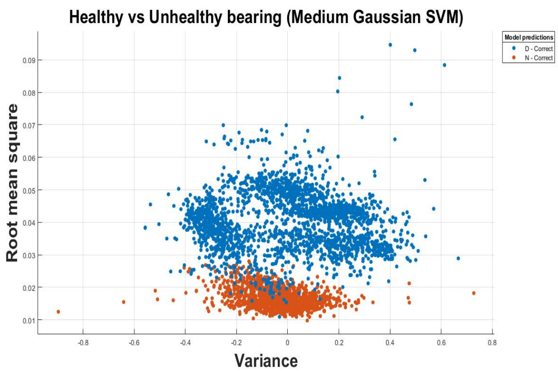

Fig.11. Scatter plot

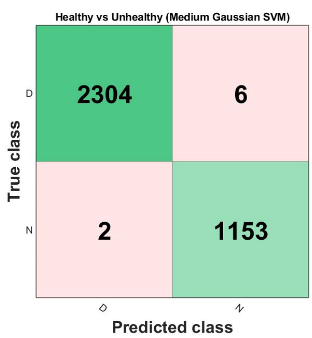

Fig.12. Confusion Matrix

V. CONCLUSION

In this research, a new practice for sorting of healthy and faulty bearing using vibration analysis is proposed. The system presented brings massive enhancement. Since only two features are used and predict faulty bearing in rotating machinery with maximum diagnostic accuracy. In addition to that, the computational complexity of our approach is quite less. There are still limitations, in the future, we aim to collect data of more faults in rotating machinery to train to classify with more faults.

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