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Selection of Best Classification Algorithm for Fault Diagnosis of Bearing using Vibration Signature Analysis

Pavan Agrawal, Pratesh Jayaswal

Abstract: ***The selection of an appropriate classification algorithm is an important issue that should be addressed in the fault diagnosis of the bearing. The vibration signatures of healthy and faulty bearings in running conditions have been acquired in time domain using FFT analyzer and convert into wavelets. The most valuable statistical features of different bearing signals are extracted from morlet wavelets and were fed to classification algorithms to classify the bearing faults. Four machine learning techniques such as artificial neural network (ANN), decision tree (DT), k- nearest neighbor (kNN), and support vector machine (SVM) are utilized as classification algorithms. Finally SVM reports the better classification outcomes than others.***

***Index Terms*: ANN, DT, kNN, Rolling element bearing, Statistical features, SVM.**

I. INTRODUCTION

Rolling element bearing (REB) is one of the most critical components among the different types of rotating machinery ranging from handheld equipment to heavy-duty industrial machinery. Sometimes minor problems can cause a bearing to fail quickly and mysteriously. Several fault diagnosis methodologies for REB have been developed by researchers [1], [2]. Vibration-based methods being prominent for diagnosing incipient defects of rotating machine elements. In an REB, a defect initiates either due to fatigue of the rolling surface or because of manufacturing errors and abrasive wear [3]–[5]. The former results in localized defects such as cracks, pits, and spalls and latter one cause distributed defects i.e., misaligned races, surface roughness, and waviness. Such defects of REB can be exhibited and explored using different signal processing techniques after acquiring the vibration signature of the test machine. Furthermore, not only the fault but also studies about the fault severity have been reported in the literature[6][7]. Vibration analysis based monitoring provides early information about the advancing malfunctions when compared with the baseline vibration signatures [8]. However, due to complicated mechanical assemblies, detection of the advancing fault becomes tedious. Under such circumstances, these vibration signals can be extensively analyzed using various signal processing techniques such as time domain, frequency domain, and time-frequency domain techniques. On applying these techniques, useful information related to the fault severity can be extracted. Statistical parameters play also a significant role in the detection of a fault of rotary machines [8][9]. It is expected from a fault diagnosis approach that it should detect as well as classify the fault with accuracy. To be precise, researchers such as Lu et al. [10] Cui et al. [11] have employed time domain signal processing techniques for bearing health monitoring. The list of time domain researches is big; however, the time domain analysis provides limited insight into the fault. Moreover, vibration signals with ample noise make may sometimes mislead the fault detection of REB. In addition to time domain analysis, many studies have been found employing statistical parameters for highlighting the impulses caused by the fault present in the complex vibration signal [12]. Sreejith et al. [13] suggested kurtosis as a suitable fault indicator when compared with peak value, RMS value, standard deviation, crest factor, impulse factor, shape factor etc. Frequency domain analysis of bearing condition analysis conducted by Amarnath et al. [14] emphasizing the use spike energy factor to exhibit the severity of fault in a bearing. In a similar way, Jayaswal et al. [15], Juan et al. [16] and Marichal et al. [17] have also detected REB fault using the insights of FFT algorithm. An assumption of Fourier transform, i.e. stationary signal can only be transformed further restricts FFT's applicability to fault diagnosis of REB [18]. Thereafter, the time-frequency analysis of bearing vibration signals have also been carried out by Khanam et al. [7], Shi et al. [19], etc. A fault diagnosis approach is always incomplete without a classification mechanism. Machine learning methods such as an artificial neural network (ANN), k-nearest neighbor (k-NN) and support vector machine (SVM) have been used for classification of various faults in an REB [20]–[27]. Authors such as Kankar et al. [28] have obtained better accuracy with Meyer and Complex Morlet wavelet for fault classification using SVM on comparison with ANN. In another work on fault diagnosis of REB by Gan and Wang [26] concluded that SVM and neural network were less efficient. Thus, it can be concluded that on the basis of selection parameters as input to the classification algorithm the responses changes. This way, it becomes complicated for an algorithm to get the most accurate result in order to detect the REB fault. All these aforementioned specific constraints motivated to define a new detection approach for mechanical vibration signals of REB.

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The proposed approach meets the aforementioned objectives, by exploiting the particular characteristics of the mechanical vibration signal. In this manuscript, an approach for fault classification of REB has been proposed. A robust approach has been developed by considering all the non-linearity in the signals and systems. Selection of mother wavelet has been demonstrated by applying the wavelet selection criterion. Initially, vibration signature of healthy and faulty bearings in time domain signals convert into morlet wavelet. Further, the statistical parameters were evaluated from the wavelet coefficients of selected wavelet. These statistical parameters were fed as input to machine learning techniques, i.e. DT, SVM, k-NN and ANN. Further with SVM classifier, statistical parameter extracted based on Morlet wavelet gives faults classification with improved efficiency

II. CLASSIFICATION ALGORITHMS

A machine learning algorithm is an approach to make artificial data and to make a prediction about data. If the target is not assigned for learning and learning takes place using self-organized data then the learning is known as unsupervised learning. In the current case study, i.e. DT, SVM, kNN Classifier and ANN are the four supervised machine learning techniques which were used.

A. Decision Tree

The decision tree is a supervised machine learning technique based on regression theory thus also known as Regression Tree. Decision Trees are binary trees and follow the decisions in the tree from the root node down to a leaf node to predict a response. Classification Tree gives a response such as ‘True’ or ‘False’ whereas the Regression Tree gives the numeric response. After extracting features from the raw vibration signal, the selection of a most suitable feature for bearing fault classification is itself a challenging task. Sugumaran et al. [29] used a decision tree for feature selection purpose and trained the fuzzy and SVM classifiers respectively.

B. Support Vector Machine (SVM)

Support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. It has been developed at first when the data had exactly two classes i.e. the concerning problem was the two-class problem where the class labels can take only two values: 1 and -1 shown in figure 1.

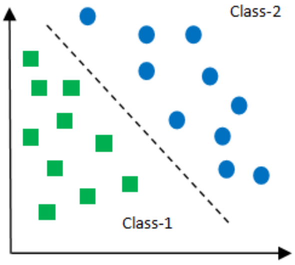

Figure 1. Support Vector Machine Classification

The present real-world problems are however more than two classes. A fault in a rolling element bearing is an illustration. There are several defects such as inner race defect, outer race defect, rolling element defect, retainer defect, and combined defect etc [30][31].

C. K-Nearest Neighbour (kNN)

k-NN categorizes objects, based on the classes of their nearest neighbors in the dataset. It is a non-parametric algorithm used for data classification. It works on the majority of neighbors vote to a query data and Euclidian distance [23]. The query data will be assigned to the most common class of k-nearest neighbors. Hence the output is the class membership. The Euclidean distance is the distance between two points’ p and q in Euclidian space. The Euclidean distance (d) in Cartesian coordinates is given by:

$$d = \sum_{i=1}^{n} \sqrt{(p_i - q_i)^2} \quad (1)$$

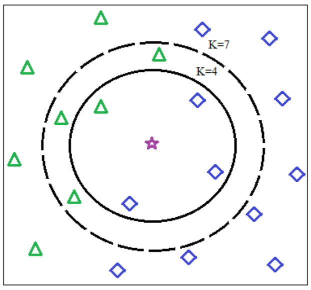

Figure 1. Schematic of kNN Algorithm

To illustrate Figure 1 can be considered in which the star may be assigned to a first class (square) or to the second class (triangles) on the basis of the value of a number of samples inside the circle (K). If K=4 (Solid circle), it will assign to first class because there are three squares and only one triangle is present inside the solid circle. If K=7, it will assign to the second class because there are four triangles and only three squares are present in dashed circle. kNN is usually determined by computing the Euclidean distance between the testing sample and each of the training samples [**Error! Reference source not found.**]. Due to the use of the Euclidean distance, the k-NN classifier is sensitive to the scaling of the feature values.

D. Artificial Neural Network (ANN)

A neural network consists of highly connected networks of neurons that relate the inputs to the desired outputs analogous to the human brain. A neuron is the smallest processing element that is connected to a number of neurons to make the neural network or Artificial Neural Network (ANN), to process.

Consequently, the structure and processing technique of ANN can perform cognition, logical inference, pattern recognition and so on [**Error! Reference source not found.**, **Error! Reference source not found.**]. The architecture of an ANN is shown in Figure 2. The weighted sum of input set is passed on to a non-linear filter called as transfer function which releases the output.

$$I = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n = \sum_{i=1}^{n} w_i x_i \quad (2)$$

Where, I= Total input received by summation unit; w_i= weights; x_i= Input to ANN

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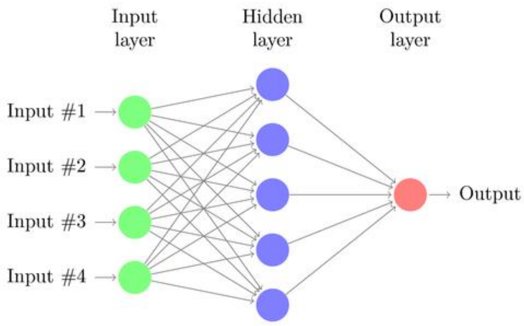


Figure 2. Operation of Artificial Neural Network

In ANN, input vectors and the corresponding target vectors are applied to train a network until it can approximate a function, associate input vectors with specific output vectors in a proper way.

III. EXPERIMENTAL INVESTIGATION

A. Test Set-Up

An SKF test rig is used to obtain vibration signatures for healthy bearing (HB) and different types of faulty bearings such as inner race fault (IRF), outer race fault (ORF), ball fault (BF), and surface roughness at inner side of outer race fault (SRF) experimentally. Test rig consists of 1 HP induction motor to facilitate variable speed up to 2900 rpm as shown in Figure . An accelerometer has been mounted on the on the rigid bearing housing. In the present case, self-aligned ball bearing (2207EKTN9) has been used. The defects were developed on different components of bearing using electric discharge drill machine.

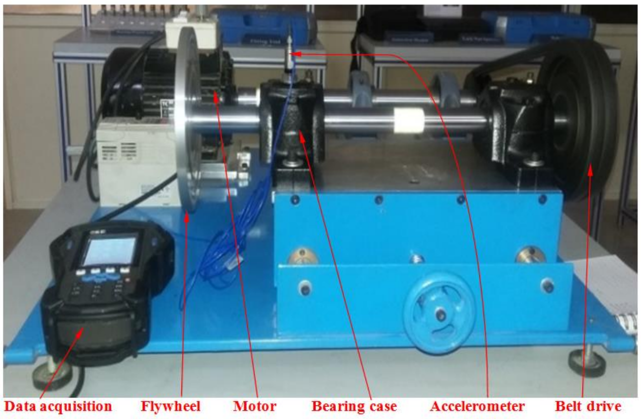
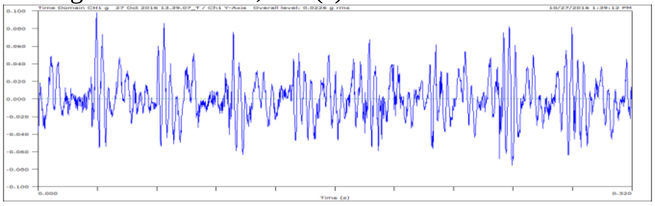


Figure 4. SKF Test Rig with Handheld FFT Analyzer

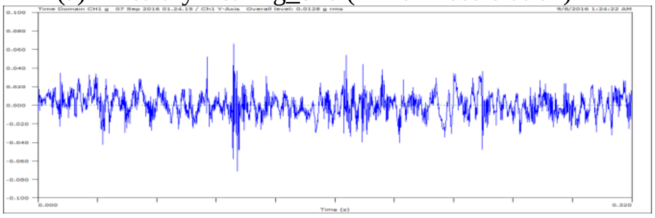
The baseline data was established by running a healthy bearing and then the data was collected for bearings with different faults using an SKF GX Series Microlog CMXA-75 (Handheld FFT analyzer).

B. Data Acquisition

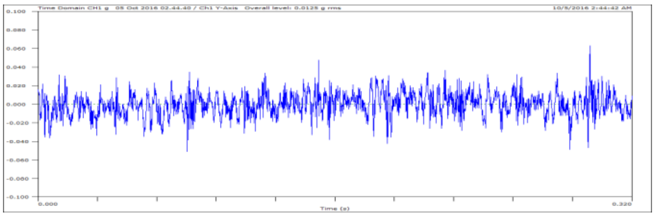
Time series vibration signals were recorded at 820 rpm and 1500 rpm for healthy bearing and bearing with defects. The sampling rate used for recording the vibration data was 6.4 kHz and the signals were recorded for 5 seconds. Periodic and low magnitude peaks are seen for the healthy bearing. The large amplitude of dispersed and non-periodic peaks must be visible for inner race defect and surface defect. Further, relatively low amplitude vibration with chaos and intermittent behavior should be observed for ball defect and outer race defect. However, such behavior was not observed from the time domain vibration signal. It implies that the time domain vibration signals of bearing fault exhibit non-stationary behavior. Thus, these signals have been analyzed using a non-stationary signal processing technique i.e., wavelet transform in the subsequent part of this work. A recorded sample of signals at 820 rpm with their FFT spectrums reported by SKF Vibration Analysis and Reporting Manager software are shown in the figure 5 in time and frequency domain for (a) healthy bearing, (b) bearing with inner race defect, (c) bearing with outer race defect, (d) bearing with ball defect, and (e) surface defect.



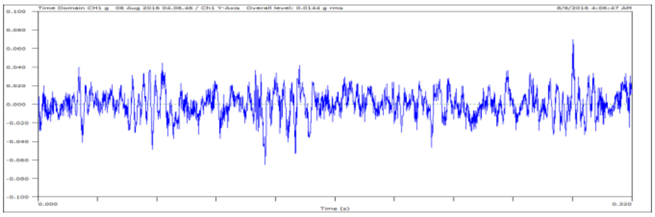
(a) Healthy Bearing_820 (Time- Acceleration)



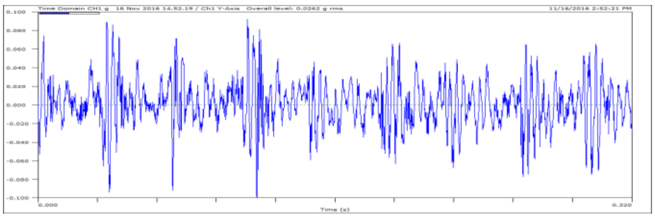
(b) Inner race fault Bearing_820 (Time-Acceleration)



(c) Outer race fault Bearing_820 (Time- Acceleration)



(d) Ball fault Bearing_820 (Time-Acceleration)



(e) Surface roughness fault Bearing_820

Figure 5 Sample vibration signals with their FFT spectrum at 820 rpm.

Periodic and low magnitude peaks are seen for the healthy bearing relatively large amplitude of dispersed and non-periodic peaks are seen for inner race defect and surface defect. Relatively low amplitude vibration with chaos and intermittent behavior is seen for ball defect and outer race defect.

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C. Feature Extraction Methodology

A rotor bearing system constitutes of a dynamic system and shows its sensitiveness towards geometrical parameters of bearing such as inner race diameter, outer race diameter, pitch circle diameter, diameter of rolling element, radial clearance, number of rolling elements carrying load, type of loading (radial, axial and combined). Acquired vibration signals were analyzed using time-frequency domain technique, i.e. wavelet transform. The morlet wavelet was selected on the high criterion that satisfies the presence of non-stationary components in the vibration signals. After the selections of morlet wavelets, statistical features were calculated based on them. Further, these statistical features were fed to the different classifiers to find out the most accurate one. This paper thus presents a fault diagnosis approach involving applicability of wavelets, statistical features and classification algorithms.

D. Feature Calculation and Fault Classification

The Morlet wavelet selected as base wavelet and CWCs of all 275 vibration signals were calculated up to 128 scales for both 820 rpm and 1500 rpm. A CWC corresponding to a signal contained high-frequency component have relatively high magnitude at a particular scale. From the beginning of vibration based health monitoring parameters such as mean value, RMS value, peak value, variance, standard deviation, skewness, kurtosis, crest factor, shape factor, impulse factor, and clearance factor etc. have been found widely explored for REB fault. These statistical measures have been found able to interpret the physical phenomenon of the fault occurring in rotating machine elements. First, second, third, and fourth statistical moments are shaped descriptors of vibration amplitude recorded from the rotor-bearing system.

E. Statistical Features

In the present investigation, eight statistical parameters viz. RMS, skewness, peak value, kurtosis, mean value, variance, standard deviation, and crest factor have been used as features to detect an incipient fault in REB. These features are as follows:

R.M.S. - It signifies the energy content within signal w. r. t. time. The root means square (RMS) is defined as the square root of the mean of the sum of the squares of signal samples [**Error! Reference source not found.**] and is given by:

$$RMS_x = \sqrt{\frac{1}{N}\left[\sum_{i=1}^{N}(x_i)^2\right]} \tag{3}$$

Where x is the original sampled time signal, N is the number of samples and i is the sample index.

Kurtosis - It is the fourth order moment normalized by the square of the variance of a signal x and gives a measure of the peak of the signal [9]. It is given by:

$$K = \frac{N\sum_{i=1}^{N}(x_i - \bar{x})^4}{\left(\sum_{i=1}^{N}(x_i - \bar{x})^2\right)^2} \tag{4}$$

For a healthy gear vibration signal, kurtosis is approximately 3.

Crest Factor - The crest factor (CF) is defined as the ratio of the maximum positive peak value of the signal x to RMS_x [**Error! Reference source not found.**] and is given by:

$$CF = \frac{x_{o-pk}}{RMS_x} \tag{5}$$

where pk is the sample for the maximum positive peak of the signal and x_{o-pk} is the value of x at pk.

Mean – The mean values of a time domain signal indicates the central tendency of the vibration data. It is evaluated as

$$\mu_x = \frac{1}{N}\left[\sum_{i=1}^{N}(x_i)^2\right] \tag{6}$$

Peak value – It highlights the highest value of vibration data. With the help of peak value, the time instances of maximum amplitude can be evaluated. It is calculated as:

$$x_{Pk} = \max(x_i) \tag{7}$$

Skewness – It is the third order moment about its mean. It measures the asymmetry of the probability distribution.

$$skewness = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{x_i - \mu}{\sigma}\right]^2 \tag{8}$$

Variance

$$\mathrm{var} = \frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N} \tag{9}$$

Standard deviation-

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N}} \tag{10}$$

The calculated sample values of these features using morlet wavelet are shown in table 1.

IV. RESULTS AND DISCUSSION

Total 50 instances for Morlet wavelet including 9 statistical features were used for both training and testing purposes of four classifiers viz. DT, SVM, KNN, and ANN. Results of these classifiers are displayed for Morlet wavelet have been presented in the form of confusion matrices. The confusion matrices had been developed using the number of test samples that are correctly classified and incorrectly classified. The actual class made the rows and predicted class made the columns of confusion matrices. The training and testing vector for Morlet wavelet has been used from the features of Table . The results of four classifiers, using Morlet wavelet (using both test set and 10 fold cross validation) are shown in Table 2 to Table 5 respectively. Table 6 exhibits the classification accuracies of classifiers. Using a test set with correct classified instances, the accuracies for DT, SVM, kNN, and

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ANN were observed as 96%, 100%, 78%, and 98% respectively. Whereas, using 10fold cross-validation set with correct classified instances, the accuracies observed for DT, SVM, kNN, and ANN were 56%, 94%, 38%, and 90% respectively. Figure 6 shows the confusion matrix of SVM without and with 10 fold cross validation.

Table 1. Performance of statistical features

RMS	Skewness	Peak	Kurtosis	Mean	Variance	Standard deviation	Crest Factor	Speed	Class
0.0674	-0.0027	0.2269	3.1437	0.0000	0.0045	0.0671	3.3665	820	HB
0.0756	-0.0022	0.2488	3.1593	0.0000	0.0057	0.0755	3.2910	820	HB
0.0809	-0.0014	0.2259	3.5551	0.0000	0.0065	0.0806	2.7921	820	HB
0.0829	-0.0006	0.2570	3.2626	0.0000	0.0069	0.0831	3.1001	820	HB
0.0820	0.0024	0.2405	2.9620	-.0001	0.0067	0.0819	2.9329	820	HB
0.0990	0.0010	0.2986	3.2095	0.0000	0.0098	0.0990	3.0162	1500	HB
0.1082	0.0004	0.3121	2.9710	0.0000	0.0117	0.1082	2.8845	1500	HB
0.1147	-0.0003	0.3152	2.7219	0.0000	0.0132	0.1149	2.7480	1500	HB
0.1175	-0.0009	0.3146	2.5247	0.0000	0.0138	0.1175	2.6774	1500	HB
0.1161	-0.0012	0.3030	2.4231	0.0001	0.0135	0.1162	2.6098	1500	HB
0.0307	-0.0059	0.1865	4.5495	0.0000	0.0009	0.0300	6.0749	820	BF
0.0323	-0.0006	0.1880	4.4704	0.0000	0.0010	0.0316	5.8204	820	BF
0.0330	0.0008	0.1861	4.3878	0.0000	0.0011	0.0332	5.6394	820	BF
0.0329	0.0010	0.1821	4.3166	0.0000	0.0011	0.0332	5.5350	820	BF
0.0320	0.0023	0.1786	4.2622	0.0000	0.0010	0.0316	5.5813	820	BF
0.0880	0.0043	0.4601	4.3951	0.0000	0.0077	0.0877	5.2284	1500	BF
0.0914	0.0034	0.6441	4.2145	0.0000	0.0084	0.0917	7.0470	1500	BF
0.0926	0.0038	0.6407	4.1481	0.0000	0.0086	0.0927	6.9190	1500	BF
0.0906	0.0014	0.6227	4.1856	0.0000	0.0082	0.0906	6.8731	1500	BF
0.0861	-0.0018	0.6225	4.3042	0.0000	0.0074	0.0860	7.2294	1500	BF
0.0225	0.0062	0.1052	5.2142	0.0000	0.0005	0.0224	4.6733	820	IRF
0.0231	0.0050	0.1554	5.2390	0.0000	0.0005	0.0224	6.7273	820	IRF
0.0232	0.0064	0.1606	6.2909	0.0000	0.0005	0.0224	6.9224	820	IRF
0.0228	0.0068	0.1631	5.3499	0.0000	0.0005	0.0224	7.1535	820	IRF
0.0218	0.0044	0.1628	6.4321	0.0000	0.0005	0.0224	7.4679	820	IRF
0.0941	0.0025	0.4775	5.6607	-.0001	0.0089	0.0943	5.0744	1500	IRF
0.1032	0.0026	0.6834	5.4485	-.0001	0.0106	0.1030	6.6221	1500	IRF
0.1087	0.0033	0.6651	6.2210	-.0001	0.0118	0.1086	6.1187	1500	IRF
0.1094	0.0035	0.6149	6.0125	-.0001	0.0120	0.1095	5.6204	1500	IRF
0.1055	0.0027	0.6342	6.8517	-.0001	0.0111	0.1054	6.0114	1500	IRF
0.0247	0.0011	0.1058	7.1894	0.0000	0.0006	0.0245	4.2842	820	ORF
0.0259	0.0011	0.1589	5.1294	0.0000	0.0007	0.0265	6.1351	820	ORF
0.0264	0.0011	0.2622	6.0906	0.0000	0.0007	0.0265	9.9318	820	ORF
0.0260	0.0015	0.2062	7.0723	0.0000	0.0007	0.0265	7.9308	820	ORF
0.0250	0.0010	0.2617	7.0954	0.0000	0.0006	0.0245	10.4680	820	ORF
0.0594	-0.0013	0.6402	6.4770	0.0000	0.0035	0.0592	10.7778	1500	ORF
0.0633	-0.0013	0.6526	5.3455	0.0000	0.0040	0.0632	10.3096	1500	ORF
0.0648	-0.0006	0.6495	6.1311	0.0000	0.0042	0.0648	10.0231	1500	ORF

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0.0640	0.0006	0.5234	6.8873	0.0000	0.0041	0.0640	8.1783	1500	ORF
0.0615	0.0013	0.5205	7.6738	0.0000	0.0038	0.0640	8.4631	1500	ORF
0.0874	0.0032	0.6211	4.0534	0.0000	0.0076	0.0615	7.1064	820	SRF
0.0972	0.0012	0.6563	5.9403	-.0001	0.0095	0.0874	6.7521	820	SRF
0.1022	0.0040	0.6740	5.8256	-.0001	0.0105	0.0972	6.5949	820	SRF
0.1020	0.0030	0.6684	4.6660	-.0001	0.0104	0.1022	6.5529	820	SRF
0.0972	0.0034	0.7486	5.3824	-.0001	0.0094	0.1020	7.7016	820	SRF
0.1092	0.0000	0.7474	5.0041	-.0001	0.0119	0.0972	6.8445	1500	SRF
0.1172	0.0012	0.8497	6.7767	-.0001	0.0137	0.1093	7.2500	1500	SRF
0.1222	-0.0007	0.8492	5.4200	-.0001	0.0149	0.1172	6.9493	1500	SRF
0.1239	-0.0002	0.8474	6.0562	-.0001	0.0154	0.1223	6.8391	1500	SRF
0.1221	0.0004	0.7436	5.7576	-.0001	0.0149	0.1240	6.0897	1500	SRF

Table 2. Confusion matrix for decision tree using Morlet wavelet

Using test set						**Using 10-fold cross validation**					
BF	**IRF**	**ORF**	**SRF**	**HB**	**Classified as**	**BF**	**IRF**	**ORF**	**SRF**	**HB**	**Classified as**
10	**0**	**0**	**0**	**0**	**BF**	**3**	**1**	**5**	**0**	**1**	**BF**
0	**9**	**0**	**1**	**0**	**IRF**	**0**	**7**	**1**	**2**	**0**	**IRF**
0	**0**	**10**	**0**	**0**	**ORF**	**5**	**0**	**5**	**0**	**0**	**ORF**
0	**0**	**0**	**9**	**1**	**SRF**	**0**	**2**	**0**	**7**	**1**	**SRF**
0	**0**	**0**	**0**	**10**	**HB**	**1**	**2**	**1**	**0**	**6**	**HB**

Table 3. Confusion matrix for SVM using Morlet wavelet

Using test set						**Using 10-fold cross validation**					
BF	**IRF**	**ORF**	**SRF**	**HB**	**Classified as**	**BF**	**IRF**	**ORF**	**SRF**	**HB**	**Classified as**
10	**0**	**0**	**0**	**0**	**BF**	**9**	**0**	**1**	**0**	**0**	**BF**
0	**10**	**0**	**0**	**0**	**IRF**	**0**	**9**	**0**	**0**	**1**	**IRF**
0	**0**	**10**	**0**	**0**	**ORF**	**0**	**0**	**10**	**0**	**0**	**ORF**
0	**0**	**0**	**10**	**0**	**SRF**	**0**	**1**	**0**	**9**	**0**	**SRF**
0	**0**	**0**	**0**	**10**	**HB**	**0**	**0**	**0**	**0**	**10**	**HB**

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Figure 6 Confusion matrix diagram of SVM without and with validation

Table 4. Confusion matrix for kNN using Morlet wavelet

Using test set						Using 10-fold cross validation					
BF	IRF	ORF	SRF	HB	Classified as	BF	IRF	ORF	SRF	HB	Classified as
7	0	3	0	0	BF	2	0	5	0	3	BF
0	10	0	0	0	IRF	0	7	0	3	0	IRF
1	0	9	0	0	ORF	5	0	3	0	2	ORF
0	3	0	7	0	SRF	0	6	0	4	0	SRF
0	1	2	1	6	HB	3	1	2	1	3	HB

Table 5.Confusion matrix for ANN using Morlet wavelet

Using test set						Using 10-fold cross validation					
BF	IRF	ORF	SRF	HB	Classified as	BF	IRF	ORF	SRF	HB	Classified as
9	0	1	0	0	BF	9	0	0	0	0	BF
0	9	1	0	0	IRF	0	8	0	0	0	IRF
0	0	10	0	0	ORF	1	1	9	0	0	ORF
0	0	0	10	0	SRF	0	0	0	10	0	SRF
0	0	0	0	10	HB	0	0	0	0	8	HB

Table 6. Evaluation of success of prediction using Morlet wavelet

Parameters	Complex Tree		SVM	
	Test set	10 fold cross-validation	Test set	10 fold cross-validation
Instances classified correctly	48 (96%)	28 (56%)	50 (100%)	47 (94%)
Instances classified incorrectly	02 (4%)	22 (44%)	00 (0%)	03 (6%)

Total instances	50 (100%)	50 (100%)	50 (100%)	50 (100%)

Table 6 (Cont.) Evaluation of the success of prediction using Morlet wavelet

Parameters	kNN		ANN	
	Test set	10 fold cross-validation	Test set	10 fold cross-validation
Instances classified correctly	39 (78%)	19 (38%)	49 (98%)	45 (90%)
Instances classified incorrectly	11 (22%)	31 (62%)	00 (0%)	05 (10%)
Total instances	50 (100%)	50 (100%)	50 (100%)	50 (100%)

V. CONCLUSION

This paper presents a complete methodology for bearing fault classification involving wavelet-based feature extraction and a classification algorithm. Different bearing defects including surface roughness were considered as test cases for investigation. Eight statistical features were calculated from the time-frequency distribution of Morlet wavelet as optimally selected wavelet. Four classification algorithms viz. decision tree, support vector machine, k-nearest neighbors and the artificial neural network had been employed for bearing fault classification. Fault classification accuracy of these classification algorithms has been compared in the present manuscript. It has been found that SVM is the most accurate of all the considered classification algorithms followed by ANN that exhibited 98% accuracy. A possible reason for better classification accuracy of SVM is due to its greater generalization capabilities. Experimental results clearly indicate that the proposed approach is able to detect and classify REB faults.

Furthermore, this study does count the effect of different loading conditions. This approach needs to be evaluated for the different loading conditions which are going to be the next objective for bearing fault diagnosis approach.

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