Journal of Artificial Intelligence Research & Advances
ISSN: 2395-6720 (Online)
Volume 6, Issue 1
www.stmjournals.com

Fault Investigation of Rolling Element Bearing using Soft Computing

Pavan Agrawal**, *Pratesh Jayaswal
Department of Mechanical Engineering, Madhav Institute of Technology and Science, Gwalior, Madhya Pradesh, India

Abstract
Rolling element bearing is the most significant mechanical component of any rotating machinery and used in vast applications from the surgical machine tool to aircraft etc. In the present research, an experimental investigation has been done using vibration analysis, continuous wavelet transform (CWT), and soft computing, i.e., support vector machine (SVM) and k-nearest neighbor (k-NN) for fault detection and diagnosis of rolling element bearing. Vibration signatures in the time domain are acquired from healthy and faulty bearings. Four complex-valued wavelets are considered. Out of four wavelets, mother wavelet is selected using relative wavelet energy (RWE) criterion and extracts the statistical features from the wavelet coefficient of raw vibration signatures. These statistical features are used as input of support vector machine and k-nearest neighbor for classification of faults. Finally, complex Morlet wavelet is selected and reports better results with support vector machine algorithm.

Keywords: *Bearing defects, vibration analysis, CWT, SVM, k-NN*

****Author for Correspondence*** E-mail: pavanmits2012@gmail.com

INTRODUCTION

The bearing of the 21st century is the outcome of precise technology and revolutionary science. When bearings fail to meet their expected life or performance level, the consequences are far-reaching and include increased downtime, high maintenance cost, and loss of revenue. It has been found that only 18% (approx.) of the bearing achieved their determined design life and other researchers also concluded that more than 50% failures of machines are occurred due to the failure of bearings. Therefore, it is necessary to find the faults of bearing at an incipient stage before failure.

Several techniques of vibration signature analysis have been given by several researchers. It is the most reliable non-destructive health monitoring technique, used to detect the location and severity of the faults. To be precise, researchers such as Lu *et al.* and Cui *et al*. have employed time domain signal processing techniques for bearing health monitoring [1, 2]. Tandon *et al*. have reviewed the vibration signature analysis and acoustic measurement methods to find out the faults in rolling element bearings using time and frequency domain and signal processing techniques such as acoustic emission and sound intensity [3]. Hassan *et al*. monitored the structural health of welded steel pipes using frequency response function and vibration based fault detection techniques [4]. Kankar *et al.* have presented the methodology to detect the severity of defects in ball bearings utilizing time domain statistical features such as kurtosis, skewness, log energy entropy, and Shannon entropy etc. [5]. The machine learning techniques such as artificial neural network and support vector machine were used as faults classifiers and found that fault classification efficiency achieved by the proposed methodology is better than other conventional methodology. Vibration analysis based monitoring provides early information about the advancing malfunctions when compared with the baseline vibration signatures [6]. 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 [7, 8]. The effectiveness of damping and stiffness of the bearing is investigated on the basis of the natural frequency of the rotor bearing system [9]. Naeini *et al.* have used the artificial neural network for pattern recognition of a control chart via statistical process control technology [10]. The wavelet transform is subdivided into the following categories such as discrete wavelet transform and continuous wavelet transform etc. There are various real and complex base wavelets like Mayer wavelet, Morlet wavelet, complex Morlet wavelet, and Daubechies wavelet etc. [11–13].

In this paper, a methodology for early fault diagnosis and classification of REB has been proposed. Selection of mother wavelet has been exhibited by applying the wavelet selection criterion. Initially, four complex-valued mother wavelets were used. It was observed from the results that, Morlet wavelet qualified the selection criteria. Further with the SVM classifier, the statistical parameters extracted based on complex Morlet wavelet gives faults classification with improved efficiency. The proposed methodology is shown in Figure 1.

VIBRATION DATA COLLECTION

In the present manuscript, an SKF experimental test rig is used to obtain vibration signatures for healthy and different types of defected bearings like inner race defect, outer race defect, and defects on rolling element or ball, and surface roughness on the outer race. Test rig consists of 1 HP induction motor to facilitate variable speed up to 2900 rpm. An accelerometer has been mounted on the rigid bearing housing. In the present case, the self-aligned ball bearing (SABB) model SKF 2207 EKTN9 has been used. Vibration signatures of healthy and defected bearings are acquired using handheld FFT analyzer. The defects were developed on different components of bearing using the electro-discharge machine (EDM). All experiments have been carried out in SKF reliability and maintenance center, MITS, Gwalior. Soft computing and code generation of proposed methodology have been done on MATLAB.

Feature Extraction

Vibration signals in terms of acceleration from bearing housing using accelerometer are acquired. The accelerometer converts the mechanical movements into analog signals and transferred to FFT analyzer. The recorded signal is sampled and converted into a discrete signal in FFT analyzer. The baseline data is established by running a healthy bearing and then the data are collected for different self-aligning ball bearings with different faults using an SKF GX Series Microlog-CMXA-75 (Handheld FFT analyzer). The signals from healthy and defective bearings are acquired at a shaft speed of 1500 rpm in the time domain. Sample signal of inner race fault bearing in the time domain is shown in Figure 2. Total 275 signals (55 of each bearing) of five bearings (one healthy and four faulty) are acquired from experimental test rig.

WAVELET TRANSFORM

Wavelet analysis is the new approach and it is used to test the health of the bearing and solving the critical problems in engineering applications. The main functions of the wavelet transform are small waves located at different times, increasing the resolution of complex signals. It also provides information on a signal in both modes (time and frequency domain).

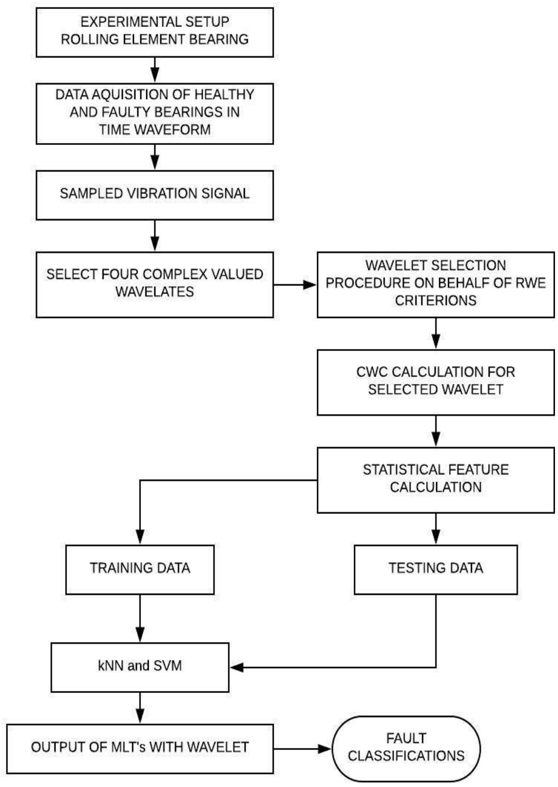


Fig. 1: *Flowchart of Fault Diagnosis Methodology.*

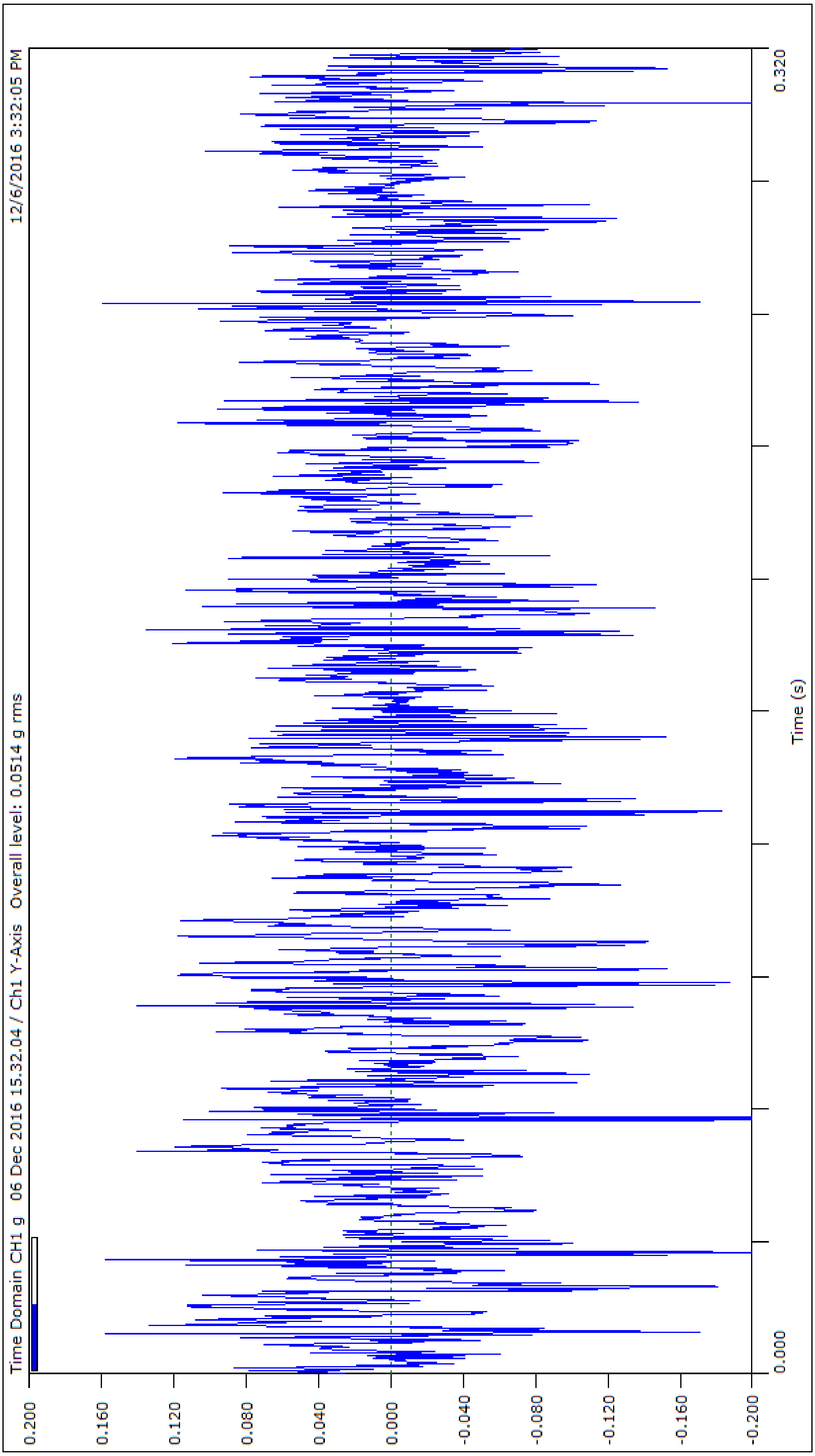


***Fig. 2:** The Signal of Inner Race Fault in the Time Domain*

The wavelet transform is subdivided into the following categories such as continuous wavelet transform, discrete wavelet transform etc. There are various real and complex base wavelets like Mayer wavelet, Morlet wavelet, complex Morlet wavelet and, Daubechies wavelet etc. [11–13]. To get desired information from raw vibration signals, each of them was then converted into their simplified form of 2^7 sub-signals. Using different four mother complex wavelets such as complex Gaussian, complex Morlet, complex frequency b-spline (fbsp) and complex Shannon (As complex-valued wavelets) the CWCs (continuous wavelet coefficients) are calculated for each signal for each bearing class. For a selection of appropriate mother wavelet, relative wavelet energy criterion is selected.

Maximum Relative Wavelet Energy Criterion

Relative wavelet energy may be considered as time-scale density to detect a defect in rolling element bearing. RWE provides the energy distribution, particularly provided to a frequency band during the calculation of CWC (Continuous Wavelet Coefficients). RWE is also able to detect similarity between short length signals. Energy content at an nth resolution of the signal is given by Eq. (1).

$$E(n) = \sum_{i=1}^{m} \left|C_{n,i}\right|^2 \qquad (1)$$

Where $C_{n,i}$ is i^{th} wavelet coefficient of n^{th} scale and m is the number of wavelet coefficients. Maximum values of RWE for the given complex-valued wavelets are shown in Table 1.

The value of RWE is seen as the maximum for complex Morlet wavelet. Hence, complex Morlet wavelet (From comp. valued wavelets) is selected as base wavelet for feature extraction for fault diagnosis of SABB. At 1500 rpm, the high value of RWE is seen for inner race fault and surface fault at the 9th scale of the 34th signal, and at the 32nd scale of 13th signal respectively using complex Gaussian wavelet as shown in Figure 3(a). A high value of RWE is seen for ball fault at the 26th scale of the 2nd signal using complex Morlet, as shown in Figure 3(b), and same for fbsp as shown in Figure 3(c). A high-value RWE is seen for outer race fault at the 128th scale of the 11th signal using complex Shannon wavelet as shown in Figure 3(d). On behalf of maximum relative wavelet energy criterion, complex Morlet is selected as mother wavelet. Calculated the statistical features like RMS, skewness, peak value, kurtosis, mean value, variance, standard deviation, and crest factor for complex Morlet at speed 1500 rpm and then fed to machine learning techniques [8, 11, 14, 15].

MACHINE LEARNING TECHNIQUES

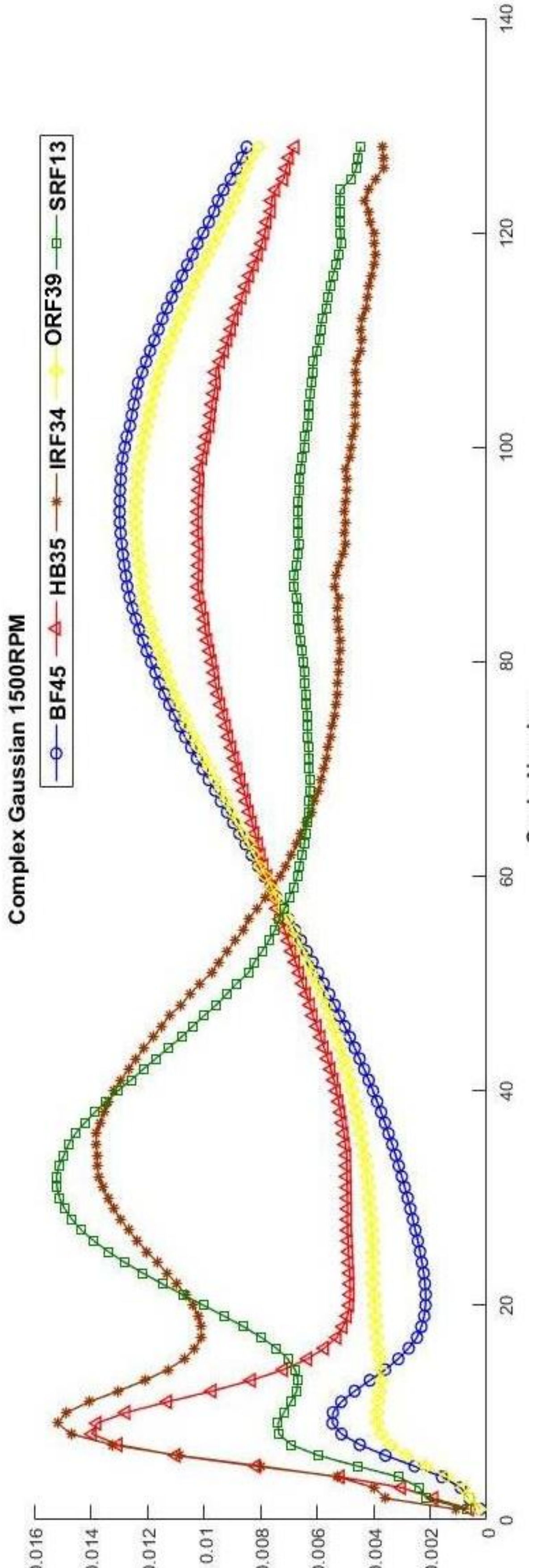
Machine learning is an approach to make an artificial model using examples (data) and to make predictions on data. It is mainly divided into two categories, supervised and unsupervised learning techniques.

K-Nearest Neighbors (k-NN)

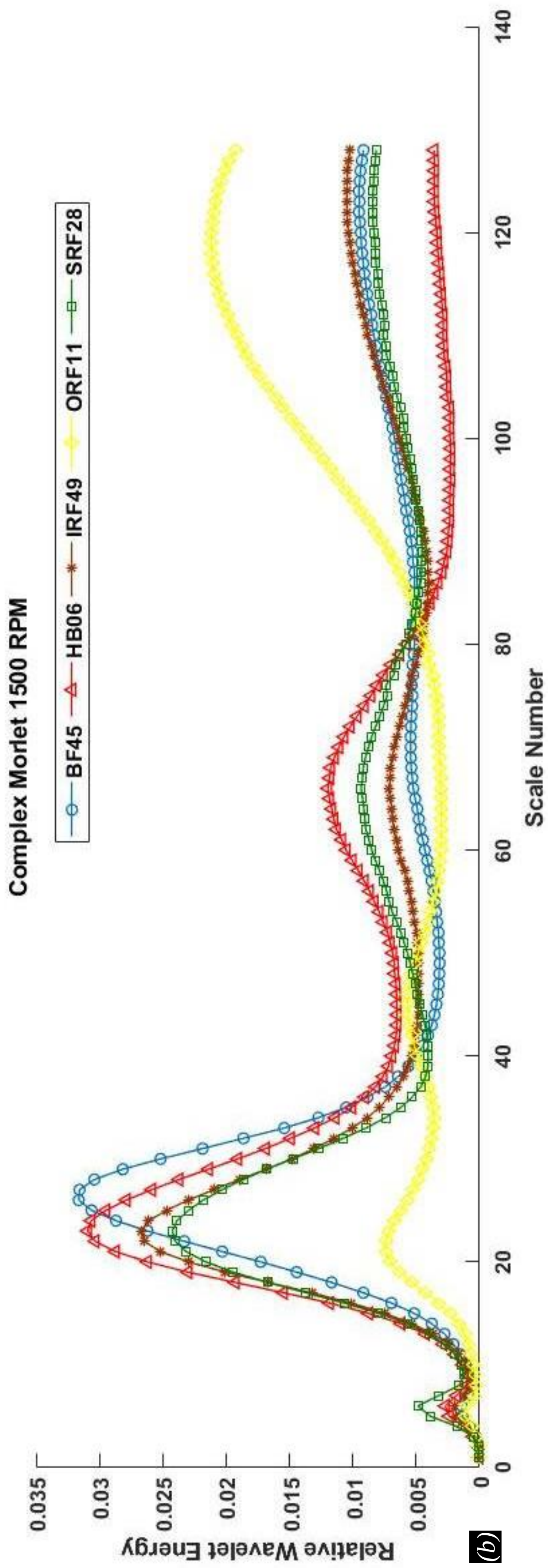
k-NN categorizes objects, based on the classes of their nearest neighbors in the dataset. K-NN is a non-parametric algorithm used for data classification. It works on the majority of neighbors votes to a query data and Euclidian distance of neighbors from the query data. The query data will be assigned to the most common class of k-nearest neighbors. Hence the output is the class membership.

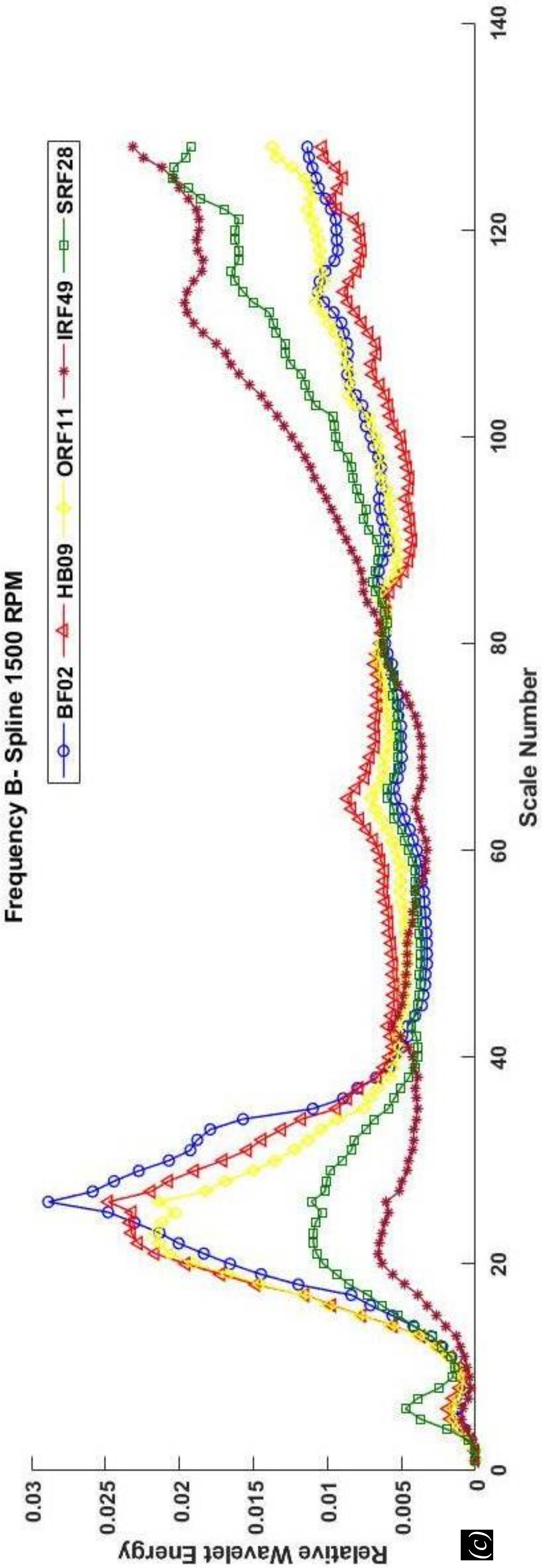
Table 1: *RWE Criterion for Complex Wavelets at 1500 rpm.*

Wavelet Type	Bearing Condition	RWE (Max)	Signal No.	Scale No.
Complex Gaussian	BF	0.0130	45	95
	HB	0.0140	35	08
	IRF	0.0152	34	09
	ORF	0.0124	39	94
	SRF	0.0152	13	32
Complex Morlet	BF	0.0316	02	26
	HB	0.0309	06	23
	IRF	0.0267	49	23
	ORF	0.0212	11	119
	SRF	0.0242	28	23
Frequency B-Spline	BF	0.0289	02	26
	HB	0.0248	09	26
	IRF	0.0217	49	23
	ORF	0.0231	11	128
	SRF	0.0204	42	125
Shannon	BF	0.0199	30	38
	HB	0.0193	02	26
	IRF	0.0177	49	26
	ORF	0.0213	11	128
	SRF	0.0162	42	125

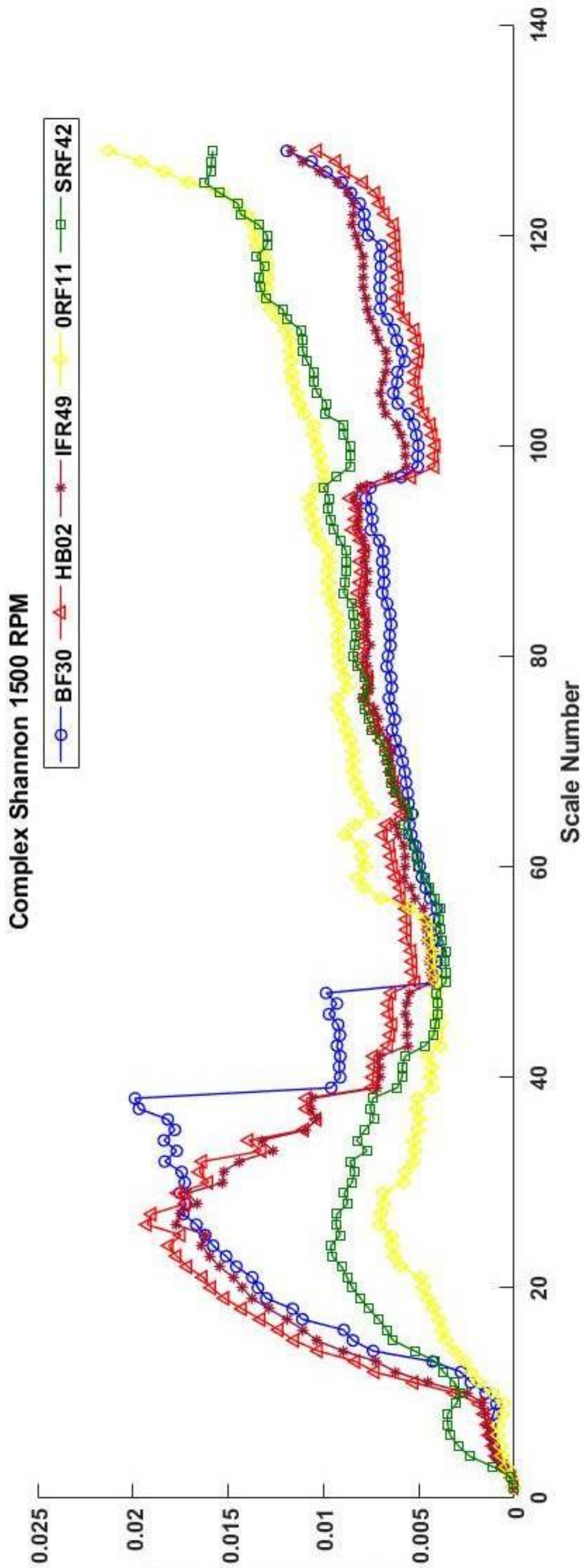

Complex Gaussian 1500RPM
BF45
HB35
IRF34
ORF39
SRF13
Relative Wavelet Energy

(a)


Complex Morlet 1500 RPM
BF45
HB06
IRF49
ORF11
SRF28
Relative Wavelet Energy
Scale Number
0
0.005
0.01
0.015
0.02
0.025
0.03
0.035
0
20
40
60
80
100
120
140
(b)


Frequency B- Spline 1500 RPM
BF02
HB09
ORF11
IRF49
SRF28
Relative Wavelet Energy
Scale Number

(c)



(d)

Fig. 3: *Graph between Relative Wavelet Energy and Scale Number at 1500 rpm for **(a)** Complex Gaussian Wavelet, **(b)** Complex Morlet, **(c)** fbsp, and **(d)** Complex Shannon Wavelet.*

The Euclidean distance is the distance between two points m and n in Euclidian space. The Euclidean distance in Cartesian coordinates is given by:

$$d = \sum_{i=1}^{n} \sqrt{(m_i - n_i)^2}$$

For example, the violet star (object) may be assigned to a first class (Blue squares) or to the second class (Green triangles) on the basis of the value of the 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 present in the solid circle. If K=7, it will assign to the second class because there are four triangles and only three squares present in the dashed circle (Figure 4).

Support Vector Machine

Support vector machine is a supervised machine learning technique. It is incorporated into learning algorithms that inspect data used for classification and regression analysis. A multi-fault SVM classifier has been used for recognition of bearing fault [16]. The SVM algorithm finds the maximum margin separating hyperplane. Kankar *et al*. have compared the machine learning techniques SOM, ANN, and SVM, and found that Mayer wavelet has given best results with SVM than other techniques [5]. The classifications of different faults are as shown in Figure 5 without and with 10-fold cross-validation.

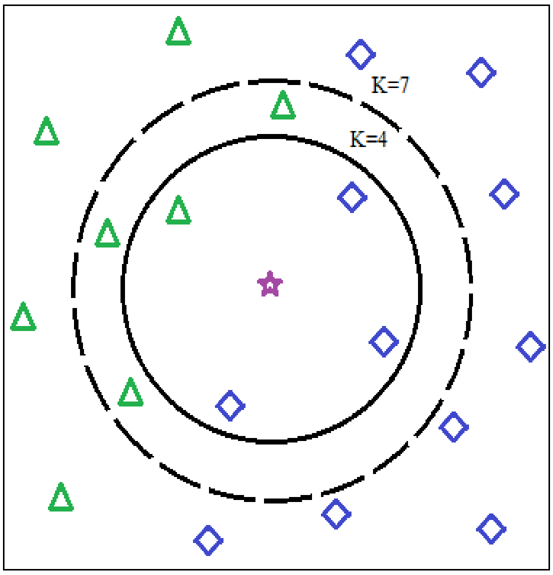


Fig. 4: *Schematic of KNN Algorithm.*

RESULTS AND DISCUSSION

Total 50 instances for each (healthy and faulty bearings) complex Morlet wavelet and nine features including speed are used for training and testing purposes. The training and testing of two classifiers as SVM and k-NN have been carried out in the present investigation. Results of these classifiers are shown in Tables 2 and 3 for complex Morlet wavelet in the form of confusion matrices. The confusion matrices are made with the number of test samples correctly classified and incorrectly classified. The actual class made the rows and predicted class made the columns of confusion matrices.

Table 4 shows the classification accuracies of the same classifiers for RWE criterion. Using test set correctly. classified instances for SVM, and kNN, are 90 and 72% respectively. Using 10-fold cross-validation set correctly, classified instances for SVM, and KNN, are 78 and 38% respectively. The scatter plot diagrams as shown in Figures 6–8 show the classification of bearing faults.

Table 2: *Confusion Matrix for SVM Using Complex Morlet Wavelet (RWE Criterion).*

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	10	0	0	0	0	BF
0	9	0	0	1	IRF	0	5	0	0	5	IRF
0	0	10	0	0	ORF	0	0	9	0	1	ORF
0	0	0	10	0	SRF	0	0	0	10	0	SRF
0	4	0	0	6	HB	0	5	0	0	5	HB

Table 3: *Confusion Matrix for KNN Using Complex Morlet Wavelet (RWE Criterion).*

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	7	1	2	0	0	BF
0	9	0	1	0	IRF	0	2	0	4	4	IRF
5	0	5	0	0	ORF	5	0	2	0	3	ORF
1	0	0	9	0	SRF	1	1	0	8	0	SRF
0	6	0	1	3	HB	0	5	1	4	0	HB

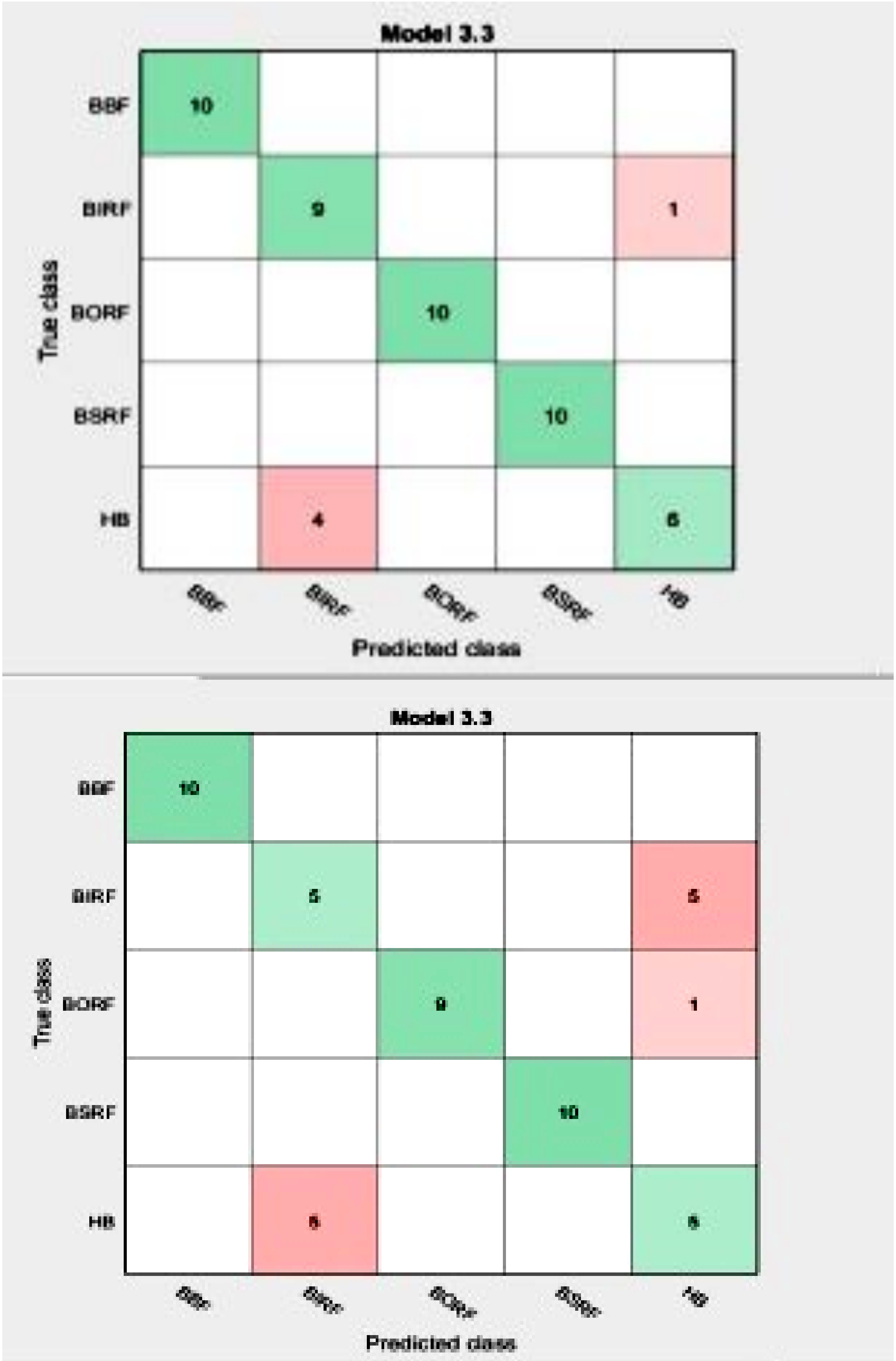


Fig. 5: *Confusion Matrix Diagrams of SVM without and with Validation (for RWE).*

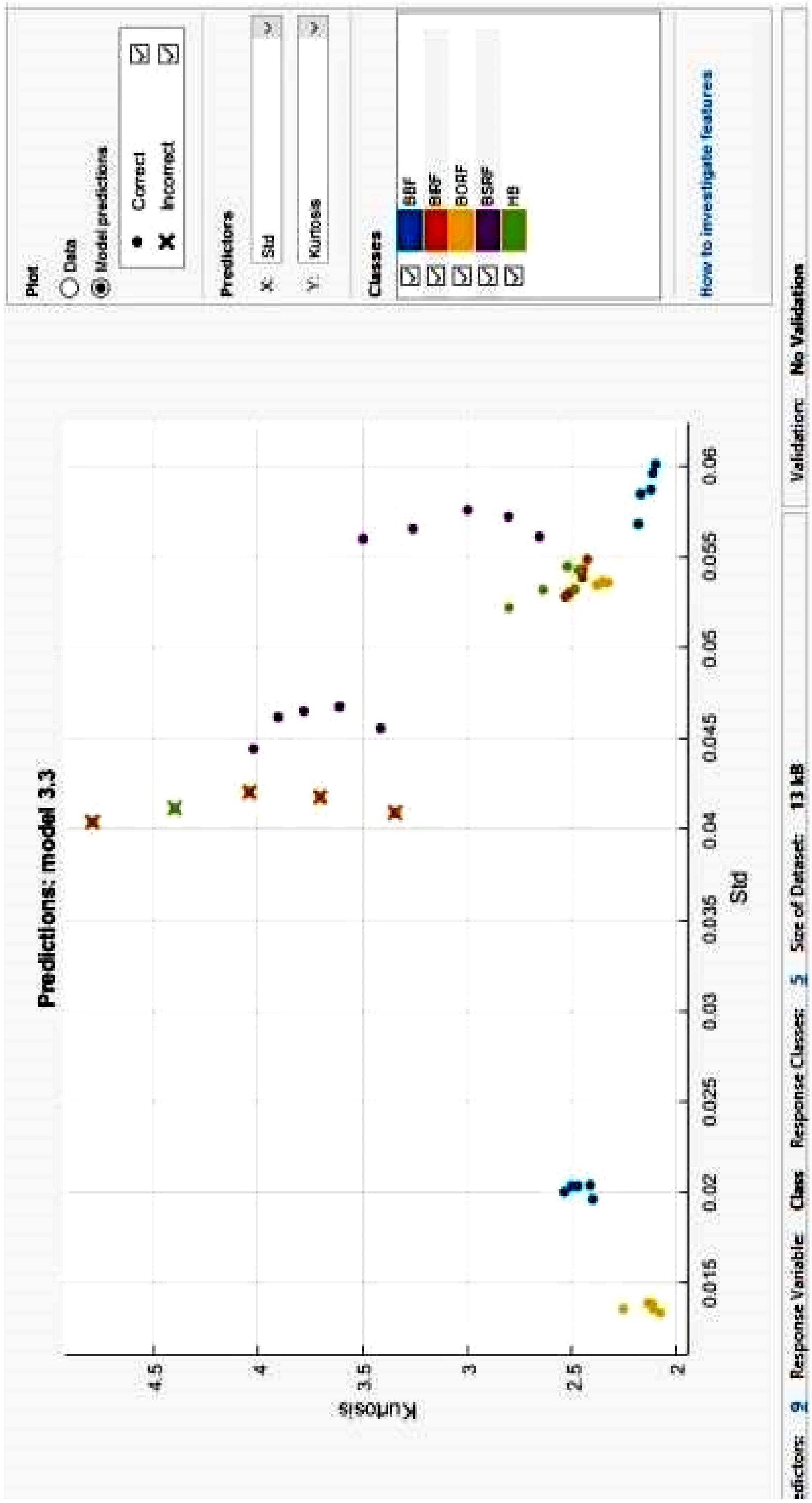


Fig. 6: *Scatter Plot Diagram of SVM for All Bearings without Validation.*

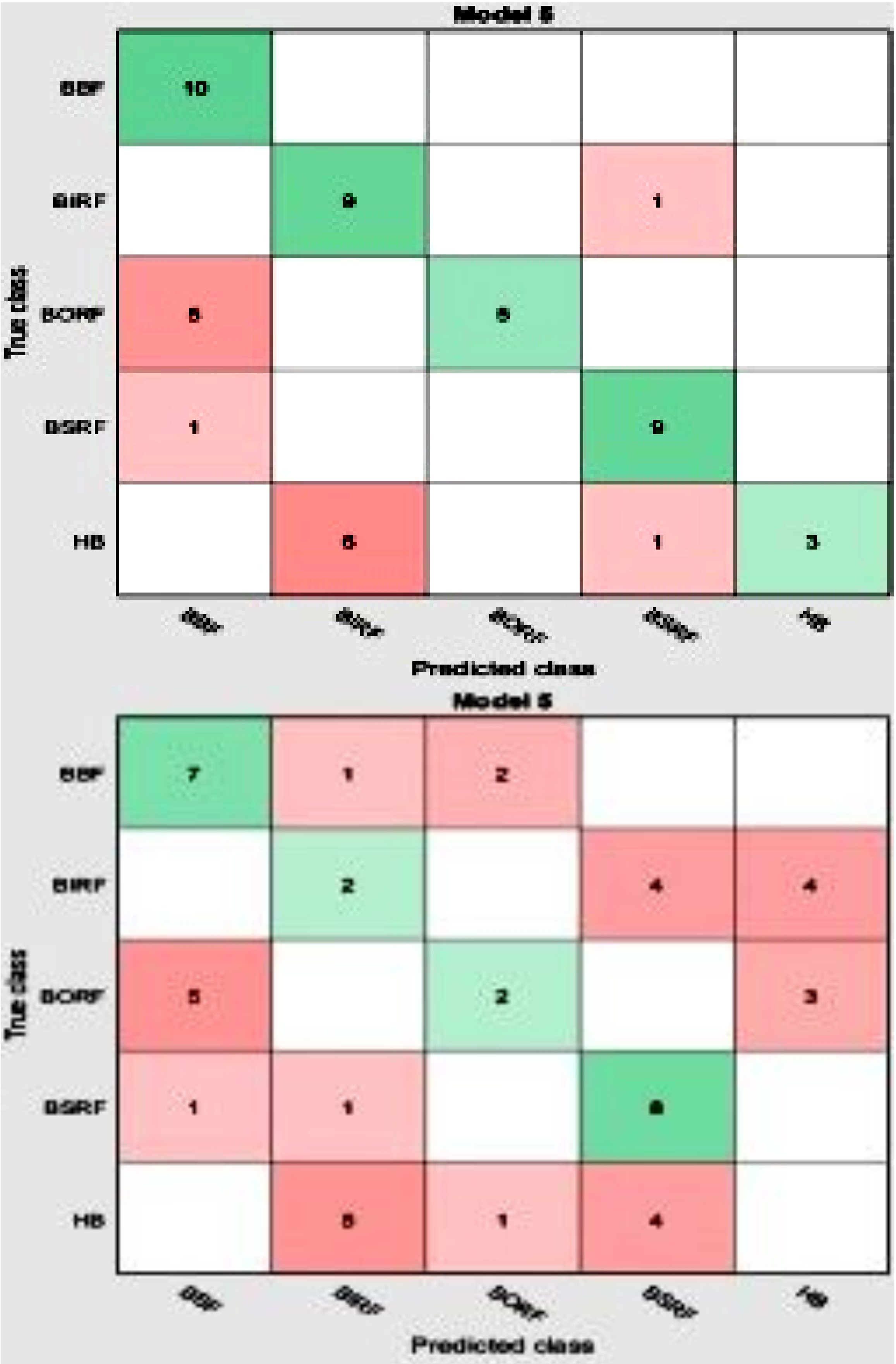


Fig. 7: *Confusion Matrix Diagrams of kNN without and with Validation (for RWE).*

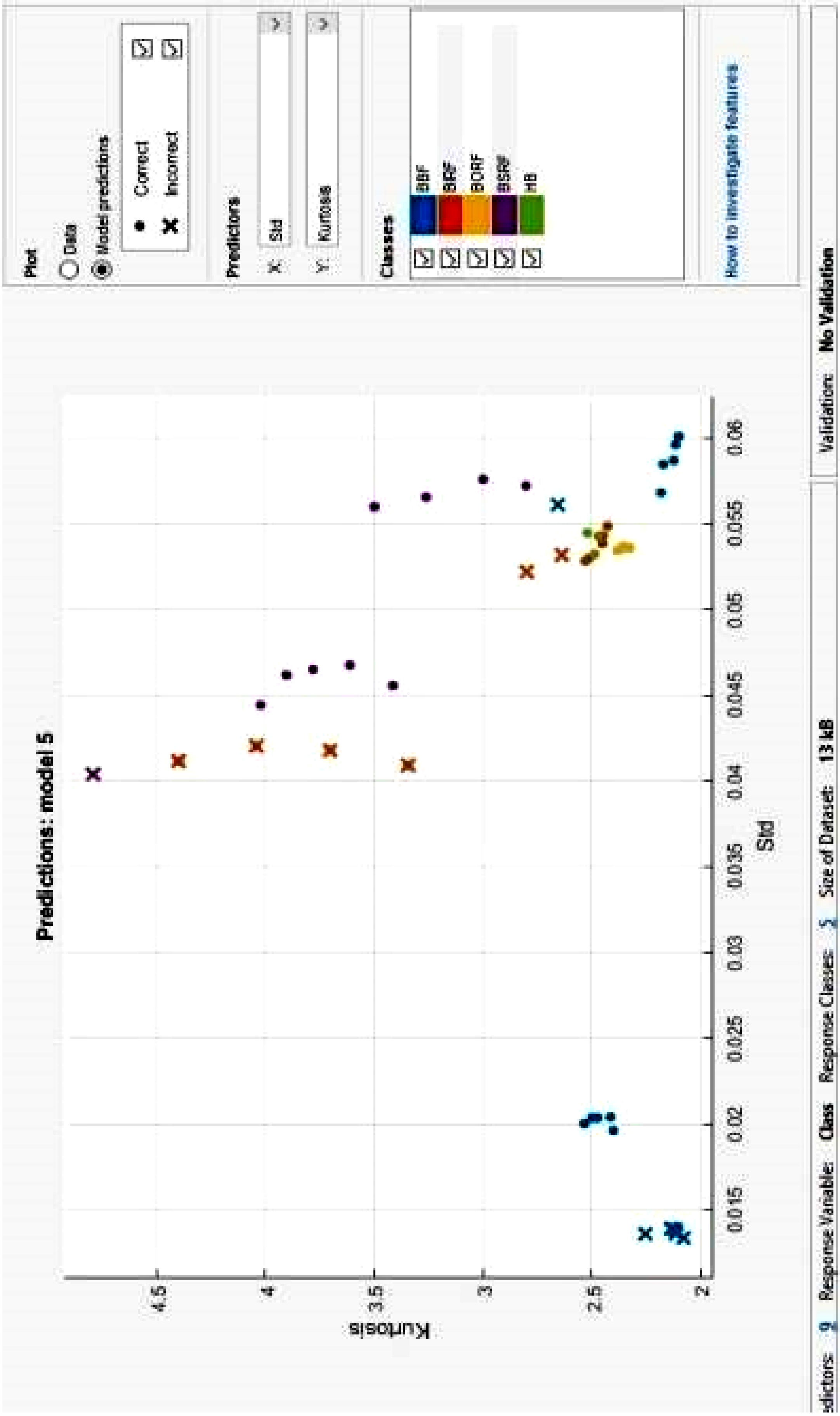


Fig. 8: Scatter Plot Diagram of kNN for All Bearings without Validation.

Table 4: *Evaluation of the Success of Prediction Using Complex Morlet Wavelet (RWE Criterion).*

Parameters	SVM		k-NN	
	Test Set	**10 fold Cross-Validation**	**Test Set**	**10 fold Cross-Validation**
Instances classified correctly	45 (90%)	39 (78%)	36 (72%)	19 (38%)
Instances classified incorrectly	05 (10%)	11 (22%)	14(28%)	10 (20%)
Total number of instances	50 (100%)	50 (100%)	50 (100%)	50 (100%)

In Figure 6 for SVM classifier, corrected classified instances are 45 and incorrect instances are 5 (cross mark). The classification performance of SVM classifier has come out best than KNN classifiers with the use of complex Morlet wavelet.

CONCLUSION

The methodology of bearing fault diagnosis is involving relative wavelet energy criterion for selection of mother wavelet. Bearing defects on the basis of defect location and generalized roughness are considered for investigation. Wavelet-based eight statistical features are calculated from vibration signals using the complex Morlet wavelet as optimally selected base wavelet among four wavelets (complex valued). Two Machine Learning Techniques (MLTs) viz. Support Vector Machine and K-Nearest Neighbors (KNN) are employed for bearing fault classification. Fault classification accuracy of these MLTs for relative wavelet energy criterion are shown in Tables 2–4 and compared. Comparative study revealed that SVM gives better classification performance than kNN. The classification accuracy of SVM is measured 90% which is better than kNN (72%) due to its greater generalization capabilities.

REFERENCES

1. Lu S, Guo J, He Q, *et al.* A Novel Contactless Angular Resampling Method for Motor Bearing Fault Diagnosis under Variable Speed. *IEEE Trans Instrum Meas*. 2016; 65(11): 2538–2550p.
2. Cui L, Zhang Y, Zhang F, *et al.* Vibration Response Mechanism of Faulty Outer Race Rolling Element Bearings for Quantitative Analysis. *J Sound Vib*. 2016; 364: 67–76p.
3. Chaudhry A, Tandon N. A Review of Vibrtion and Acoustic Measurement Methods for the Detection of Defects in Rolling Element Bearing. *Tribol Int*. 1999; 32(8): 469–480p.
4. Hassan AA, El-Wazery MS, Zoalfakar SH. Health Monitoring of Welded Steel Pipes by Vibration Analysis. *Int J Eng Trans A Basics*. 2015; 28(10): 1782–1789p.
5. Kankar PK, Sharma SC, Harsha SP. Fault Diagnosis of Ball Bearings Using Continuous Wavelet Transform. *Appl Soft Comput J*. 2011; 11(2): 2300–2312p.
6. Lee J, Wu F, Zhao W, *et al.* Prognostics and Health Management Design for Rotary Machinery Systems: Reviews, Methodology and Applications. *Mech Syst Signal Process.* 2014; 42(1–2): 314–334p.
7. Sharma V, Parey A. Case Study on the Effectiveness of Gear Fault Diagnosis Technique for Gear Tooth Defects Under Fluctuating Speed. *IET Renew Power Gener*. 2017; 11(14): 1841–1849p.
8. Jayaswal P, Wadhwani AK. Application of Artificial Neural Networks, Fuzzy Logic and Wavelet Transform in Fault Diagnosis via Vibration Signal Analysis : A Review. *Aust J Mech Eng.* 2015; 7(2): 157–172p.
9. Eftekhari M. The Effect of Damping and Stiffness of Bearing on the Natural Frequencies of Rotorbearing System. *Int J Eng*. 2017; 30(3): 448–455p.
10. Naeini MK, Bayati N. Pattern Recognition in Control Chart Using Neural Network based on a New Statistical Feature. *Int J Eng*. 2017; 30(9): 1372–1380p.
11. Bafroui HH, Ohadi A. Application of Wavelet Energy and Shannon Entropy for Feature Extraction in Gearbox Fault Detection Under Varying Speed Conditions. *Neurocomputing*. 2014; 133: 437–445p.
12. Yan R. *Base Wavelet Selection Criteria for Non-Stationary Vibration Analysis In Bearing Health Diagnosis*. Dissertation: Ph. D., University of Massachusetts Amherst; 2007.

13. Search H, Journals C, Contact A, *et al.* Failure Diagnosis and Prognosis of Rolling-Element Bearings using Artificial Neural Networks : A Critical Overview. *J Phys*. 2012; 364(1).
14. LPP, SPV, Naidu VPS, *et al.* Bearing Health Condition Monitoring : Time Domain Analysis. *2008 IEEE Reg. 10 Colloq. 3rd Int Conf Ind Inf Syst.* 2014; 75–82p.
15. Kalyan ASPHV, Bhavaraju M, Kankar PK, *et al*. A Comparative Study on Bearings Faults Classification by Artificial Neural Networks and Self-Organizing Maps using Wavelets. *Int J Eng Sci Technol*. 2010; 2(5): 1001–1008p.
16. Sui W, Zhang DAN. Rolling Element Bearings Fault Classification Based on SVM and Feature Evaluation. In *8th International Conference on Machine Learning and Cybernetics*. Jul 2009; 450–453p.

Cite this Article
Pavan Agrawal, Pratesh Jayaswal. Fault Investigation of Rolling Element Bearing using Soft Computing. *Journal of Artificial Intelligence Research & Advances*. 2019; 6(1): 8–22p.