Fault Diagnosis of Helical Gearbox through Vibration Signals using J48 Decision Tree and Wavelet

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Abstract

Objectives: Gear plays an efficient role in power transmission. Minor faults in gears can lead to severe faults. The vibration analysis can be used for determining the causes of the faults which are raised while ongoing operation. This study determines the usage of machine learning algorithm for condition monitoring of helical gearbox. **Methods/Statistical Analysis**: The vibration signals were taken by using accelerometers from helical gearbox in which artificial faults were incorporated before testing. By using Discrete Wavelet Transform (DWT) feature extraction was done. The feature selection and feature classification was done by using J48 algorithm and subsequent results were observed. **Findings:** The classification accuracy of helical gearbox using Discrete Wavelet Transform was observed to be 89.28% which itself shows its efficiency. In feature extraction maximum accuracy of 89.06% was obtained by sym 8 wavelet. During feature selection and classification many modifications in algorithm were made i.e. minimum number of object, confidence factor etc. Suitable readings of the modifications were applied and feature classification was done. **Improvements:** Different Discrete Wavelet Transforms were compared taken from vibration signal proved Sym 8 Discrete Wavelet Transform is the best one to be used in this scenario. The methodology yielded a satisfactory classification accuracy of 89.28%, which is higher than what was obtained by similar experiments with different methodology till date. The results and their analysis are discussed in the study. The performance of this methodology may be further improved by using different classifiers and different wavelets.

Keywords: Condition Monitoring, Discrete Wavelet Transform, J48 Algorithm, Vibration Signals

1. Introduction

Gear plays an important role in rotary machinery for efficient transmission of power. When multiple speeds are needed, multiple gear transmissions can be used to increase torque while slowing down the output speed. Any defect in gears may lead to sudden breakdown and hence, resulting in a severe accident. Moreover, in certain cases it affects the other parts of machinery also. Condition monitoring is very much necessary as it monitors the defects in a system. This technique provides useful and reliable information; hence, bringing cost benefits to industry. The objective is to investigate the correlation among vibration analysis, wavelet features and fault diagnosis of the helical gearbox.

Condition monitoring displays the actual asset to decide what technique will be suitable for maintenance. As gears are the components which are always found in rotation machinery frequently, its failure or small defect can disturb the complete system. Also the detection of gear failure at the correct time is of the utmost importance otherwise system may sustain a bigger loss. This paper talks about various defects occurring in helical gearbox[1]. Generally helical gearbox is robust and reliable device. This problem is because of application error. It may be because of mounting and installation of gear system, vibration, lubrication, etc. The most collective problem originate in helical gearbox is misalignment[2,3]. Due to misalignment, the pinion and gear is not meshing properly during operation which leads

to high stress concentration at surface of gears, therefore, resulting in tooth damage of gears, wear and tear, excessive heat generation, etc. When the helical gearbox is working under many speeds and loads, the amount of severity of faults is difficult. So, vibration, sound and acoustic emission signals are used for fault detection. The fault diagnosis using machine conditioning consists of three stages specifically, feature extraction, feature selection and feature classification. The features may be statistical features, histogram features or wavelet features, of which wavelet features are considered in the present study.Techniques for feature selection include Principal Component Analysis (PCA), Decision Tree (DT), Artificial Neural Network, Genetic Algorithm (GA), etc. Decision Tree feature selection technique was used in the present study. They are compact and easy to understand and can identify the best features from the data set. The selected features are then classified using various machine learning algorithms. Naïve Bayes and Bayes net algorithms were reported for categorizing the faults in helical gearbox[4]. The Naïve Bayes and Bayes net based models have a drawback. These classifiers need a big data set in order to make reliable estimation of the probability of each class. If the Naïve Bayes classification algorithm is used with a small data set the precision will be very low. Fault diagnosis of helical gearbox using variational mode decomposition with Naïve Bayes and Bayes Net classifiers through vibration signals have given a good classification accuracy[5]. In another study a prototypical for fault diagnosis approach using Decision Tree have been reported for helical gearbox. Gear fault detection using vibration analysis and continuous wavelet transform was developed with continuous wavelet transform[6]. The conventional vibration spectrum analysis is frequency domain based signal which cannot foretell the frequency at a specified time whereas by using Discrete Wavelet Transform the signal belonging to time domain is connected to time-frequency domain information. A fault diagnosis approach was developed for gear fault diagnosis through discrete wavelet features based on Decision Tree and Support Vector Machines[7]. In a reported study classified the faults in spur and bevel gear using the Morlet wavelet features with SVM and PSVM[8]. Gear damage diagnosis study was attempted using Support Vector Machines[9]. The drawback of Support Vector Machine classifier is that (SVM'S) are not efficient if the number of features is very high in number compared to the training samples. Moreover, SVM algorithm doesn't perform well on highly skewed data sets. If the data sets are such that they arrive in batches and regular incremental learning model is required

then SVM is not a good option for incremental learning. A fault diagnosis approach using vibrational signals based on Decision Tree assisted intelligent controller was developed for the find faults in gearbox[10]. A prior study examined fault diagnosis model for gearbox which is based on wavelet and Support Vector Machine with immune Genetic Algorithm[11]. In this approach Empirical mode decomposition was used for feature extraction and Immune Genetic Algorithm was also used to select appropriate free parameters for wavelet. A dynamic based wavelet tool was developed for gearbox fault diagnosis[12]. Another model was proposed for spur bevel gear fault diagnosis using discrete wavelet features and Decision Tree classification[13]. However, In this model condition monitoring was done on the spur, bevel gearbox and only one family of wavelet feature is employed, i.e. debauchee wavelet. In this study, all the seven families of wavelets were selected for the fault diagnosis of helical gearbox. The classifier model has to be chosen in such a way that it should give higher classification accuracy with minimum training time. Hence, the results are compared with the Decision Tree algorithm and the discussions are presented.

2. Experimental Studies

The test rig setup was built to study fault diagnosis of helical gearbox. The details about the new setup and new procedure are conversed in the subsequent subdivision.

2.1 Experimental Setup and Procedure

The experimental setup is shown in Figure 1. The system consists of 5 HP two stage helical gearbox. The gearbox is driven by a 5.5 HP, 3-phase induction motor with a speed of 1440 RPM. For the present-day study, the motor operates at 80 RPM. The speed of the motor is organized by an inverter
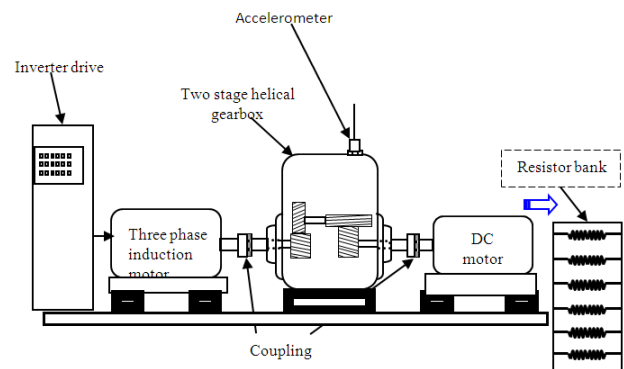

Figure 1. Experimental setup of helical gearbox.

drive. With a step up ratio of 1:15, the speed of the pinion shaft in the second stage of gearbox is 1200 RPM. The instantaneous of specification of test rig is given in Table 1. The pinion is linked to a DC motor to generate 2 KW power, hence, is dissolute in a resistor bank. Therefore, the actual load on the gearbox is only 2.6 HP which is 52% of its rated power 5 HP. Use of load in manufacturing atmosphere varies from 50% to 100%. Due to torque variations, additional torsional vibrations can occur. This is avoided in this case by using DC motor and resistor bank. To restrict backlash to the gears in the structure, the electrical machines are fitted with the tyre couplings. The motor, gearbox and generator are riding on I-beams, which are attached to a massive basis. The dimension of vibration signals was taken by in accelerometer which is connected close to the test bearing. The sampling frequency of 8.2 kHz, was fixed which is based on NY Quist sampling theorem. The length of sample signal is 8192 (2^{13}). Total number of sample signals is 448 and each class consists of 64 sample signals. Local faults are categorized in three lessons. 1. Surface wear, 2. Cracked tooth and 3. Loss of a portion of the tooth due to flouting of the tooth at the root or at a point on employed tip. Different approaches can be functional to simulate faults in gear via; Electric Discharge Machining (EDM), grinding and adding iron particles in the gearbox lube. Partial tooth removal is the humblest method to simulate faults in gear. This pretends the partial tooth break, which is common in many industrial applications. The signals were recorded by using accelerometers. The recorded signals were then used for feature extraction using MATLAB through different wavelet structures. The mined structures were then categorized by Decision Tree classifier.

Table 1. Specifications of helical gearbox

	First stage	Second stage
Number of teeth	44/13	73/16
Pitch circle diameter (mm)	198/65	202/48
Pressure angle	20	20
Helix angle	20	15
Modules	4.5/5	2.75/3
Speed of shafts	80 RPM (input)	1200 RPM (output)
Mesh frequency	59 Hz	320 Hz
Step-up ratio	1:15	
Rated power	5 HP	
Power transmitted	2.6 HP	

3. Feature Extraction

For fault diagnosis, the analysis of vibration signals was taken. Moreover, the signal obtained was time-domain signal. By Discrete Wavelet Transform (DWT), the signal fitting to time domain was linked to time-frequency domain info. The procedure of wavelet decomposition was achieved on vibration signals using Discrete Wavelet Transform (DWT). The trends and details were the consequence of decomposition. For next level trend and detail, the previous trends obtained from decomposition were decomposed again. This is how, previous level trends were decomposed and many levels of details were obtained. The length of the signal is 8192 (2^{13}) and possible decomposition levels are 13. At each level, the detail coefficients were used to compute the energy content using the following formulae:

$$V_i = \sum_{i=1}^{n} X_i^2$$

Where $x_{i=}$ details coefficients; n=number of detail coefficients.

Then the features were defined as the energy content at each level. The feature vector is defined as:

$$V = (v1, v2, v3,………,vm)$$

When m – (number such that length of signal) = 2^m

$v1, v2, v3…$ are energy content at given level

Families of wavelets taken into account for the fault diagnosis are:

- Haar wavelet.
- Discrete Meyer wavelet.
- Daubechies wavelet – Db1,db2, db3, db4, db5, db6, db7, db8, db9, db10.
- Biorthogonal wavelet – bior1.1, bior 1.3, bior 1.5, bior 2.2, bior 2.4, bior 2.6, bior 2.8, bior 3.1, bior 3.3, bior 3.5,bior 3.7, bior 3.9, bior 4.4, bior 5.5, bior 6.8.
- Reversed Biorthogonal wavelet - rbio1.1, rbio 1.3, rbio 1.5, rbio 2.2, rbio 2.4, rbio 2.6, rbio 2.8, rbio 3.1, rbio 3.3, rbio 3.5, rbio 3.7, rbio 3.9, rbio 4.4, rbio 5.5, rbio 6.8.
- Coiflet – coif 1, coif 2, coif 3, coif 4, coif 5.
- Symlets – sym 2, sym 3, sym 4, sym 5, sym 6, sym 7, sym 8.

4. Wavelet Selection

For wavelet selection, time–domain signals were processed from seven wavelet families using 54 different discrete wavelet. The extracted features were classified through J48

Decision Tree algorithm using Weka 3.6 and maximum classification accuracy was obtained Figure 2 to Figure 7. Sym wavelet 8 gave the best classification accuracy when classified through J48 Decision Tree as compared to all DWT's mentioned above. The symlet N, is also called as sym N, where N is the order. The characteristics of sym wavelet can be defined as compactly supported wavelets with least symmetry and highest act of vanishing moments for a given support width *i.e.* 2N-1. The filter length is 2N. For point and orthogonality conditions, the possible

solutions are 2N-1. Hence, the highest produced scaling filter of solution is selected as the outcome. The highest wavelet feature was selected from each of the discrete wavelet features namely – Bior, Coif, DB, Dmey, Haar, Rbio, Sym and graph was plotted as shown in Figure 8. The graph plot represents, (SYM 8) wavelet feature has the highest classification accuracy of 89.06% as compared to other discrete wavelet features.

5. Feature Selection

Feature selection was carried out by applying a Decision Tree algorithm. The mined structure was applied as inputs for feature selection. In this paper, J48 Decision Tree was used for feature selection and classification. Feature classification was done using J48 Decision Tree algorithm and Decision Tree was obtained. Among all 13 features, 7 features were selected using Decision Tree as shown in Figure 9, as these features were donating more in fault diagnosis of helical gearbox as compared to other features.
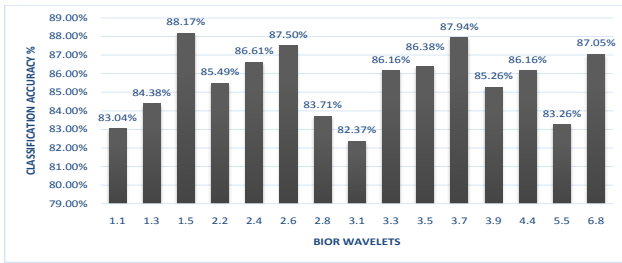

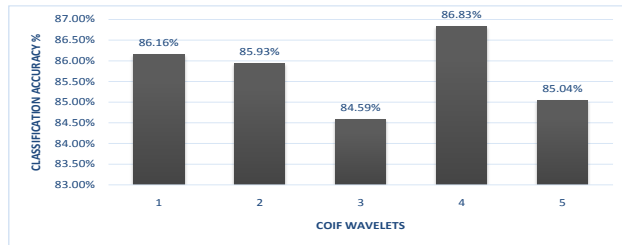**Figure 2.**   Bior wavelets vs. classification accuracy %.

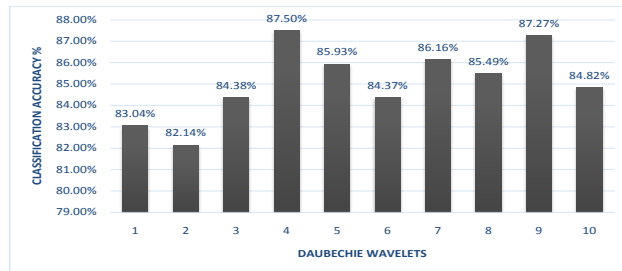**Figure 3.**   Coif wavelets vs. classification accuracy %.

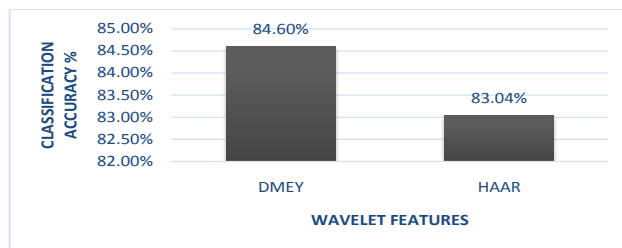**Figure 4.**   Daubechie wavelet vs. classification accuracy %.
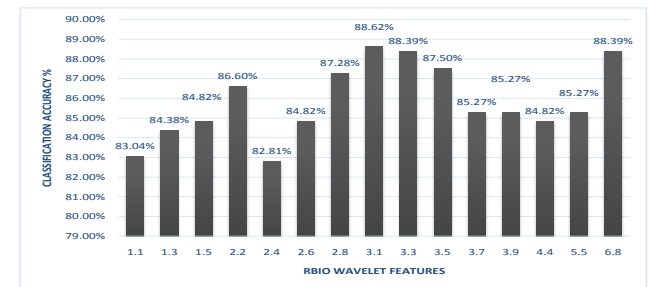

Figure 5.   Dmey and Haar vs. classification accuracy %.

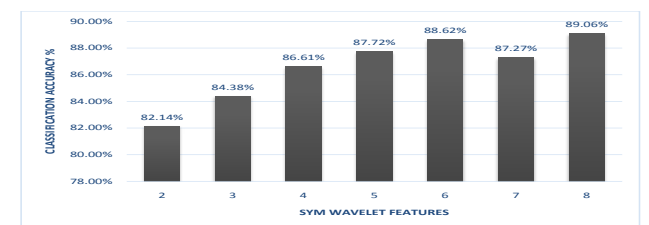**Figure 6.**   Rbio wavelet vs. classification accuracy %.

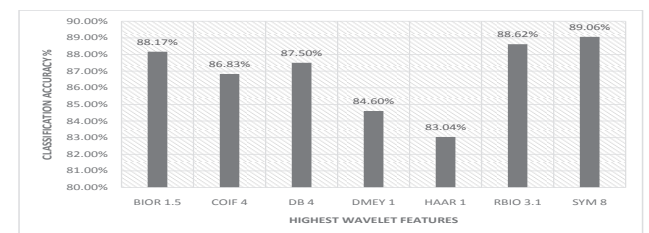**Figure 7.**   Sym wavelet vs. classification accuracy %.

Figure 8.   Classification accuracy of wavelet.

Among all 13 features, the influence of v3 feature alone was 52.45% in fault diagnosis of helical gearbox. It is also called as root node as it is the top most first piece in Decision Tree. Then top two features v3, v10 were selected in Decision Tree and classification accuracy of 65.40% was obtained. This was repeated for v3, v10, v1 and classification accuracy of 76.11% was obtained. For v3, v10, v1, v6 classification accuracy of 78.57% was obtained. Again for v3, v10, v1, v6, v5 classification accuracy of 83.70% was obtained. For v3, v10, v1, v6, v5, v4 classification accuracy of 86.60% was obtained. For v3, v10, v1, v6, v5, v4, v2 classification accuracy of 89.28% was obtained which is the highest. For v3, v10, v1, v6, v5, v4, v2, v7 classification accuracy of 89.28% was obtained, hence it can't be considered as highest classification accuracy. Here, highest classification accuracy with less number of features is given importance. Again for further features classification accuracy was taken. So, 7 features with highest classification accuracy were selected during the process of feature selection. The results were plotted in Figure 10. From the graph in Figure 10, it is clear that all seven features which are v3, v10, v1, v6, v5, v4, v2 are giving maximum classification accuracy.

6. Feature Classification

The process of feature classification was done by J48 Decision Tree algorithm. J48 Decision Tree is methodology
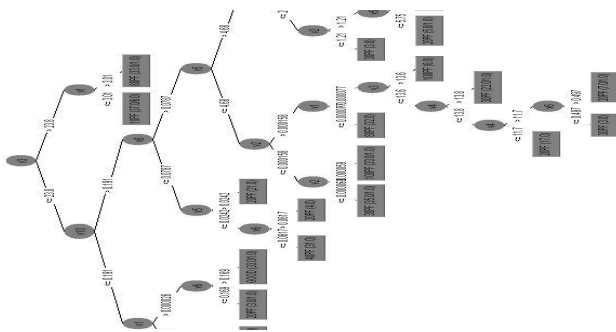

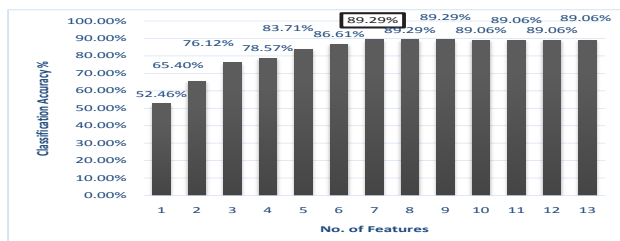**Figure 9.**   Decision Tree with selected seven features.

Figure 10.   Classification accuracy vs. no. of features.

consisting of branches, roots, nodes and leaves to define classification rules. J48 has two phases named as building and pruning phase. For building phase, the tree has a single root node for the entire training set. A new node is attached to Decision Tree for every partition. J48 uses entropy based information gain as the selection criteria. Entropy is said as the measurement of uncertainty in random variables. The information gain is given by partitioning of the features which is due to the reduction in entropy. Information gain (*S,A*) of a feature *A* relative to a collection of examples *S*, is defined as:

$$Gain\ (S,\ A) = Entropy\ (S) - Entropy\ (Sv) \qquad \sum_{v \in Values\ (A}^{n} \frac{Sv}{S} \quad (1)$$

Where $Sv = (\{s \in S| \ A(s) = m\})$.

Entropy is a measure of homogeneity of the set of examples and it is given by:

$$Entropy\ (S) = \sum_{i=1}^{c} - Pi\ log_2 Pi \qquad (2)$$

Where '*Pi*' is the proportion of '*S*' belonging to the class '*I*' and '*c*' is the number of classes.

The second term in the equation above is the expected entropy after *S* is partitioned using feature *A*. When the data becomes large, the Decision Tree becomes large leading to more inaccuracy due to underfitting or over-training. Thus for better classification accuracy, the trees must be pruned to remove less reliable branches. This is usually done by removing the features which contribute negligibly to the classification. For more details of J48 Decision Tree refer.

7. Results and Discussion

Vibration signals were developed in normal and abnormal circumstances of helical gearbox using accelerometer. Total 448 samples were collected and 64 examples were from good circumstance. From 10%, 20%, 30%, 40%, 80% and 100% fault conditions, 64 samples each were collected. The wavelet features were calculated and act as the input to the algorithm. For article selection and cataloguing, the Decision Tree J48 algorithm was employed with this dataset. The produced conclusion tree is offered in Figure 9. The disorder of gearboxes *i.e.* classes are characterized by rectangle. In rectangle the info about the condition is rendered by using truncations e.g.: -'GOOD', '10PF', '20PF', '30PF', '40PF', '80PF' and '100PF'. There are two numbers separated by a slash. The first number stands for the quantity of data points that provision choice that implies

how many data points will be organized out correctly is given as the first act. After slash, the second bit is elective and it stands for the amount of data points that are in contradiction of the rule adopted. The classification accuracy for different families of wavelets were calculated and compared as shown in Figure 8. Bior1.5 (88.17%), coif 4 (86.83%), db 4 (87.50%), dmey (84.60%), haar (83.04%), rbio 3.1 (88.62%) and sym 8 (89.06%) are maximum classification accuracy obtained for each wavelet family. It is clear that sym 8 is having highest classification accuracy as compared to other discrete wavelet features. There are total 448 sample signals taken for feature classification. 64 sample signals were classified employing J48 Decision Tree algorithm. The parameters which were varied to obtain highest classification accuracy with selected seven features v1, v2, v3, v4, v5, v6 and v10 were minimum number of objects and confidence factor. The minimum number of objects can be defined as minimum number of instances per leaf whereas confidence factor is used for pruning. Smaller values incur more pruning. At first, confidence factor was kept as constant and minimum number of objects was varied within the range of (1-30) value as after 30, the classification accuracy was drastically reduced. For value 1 of minimum number of objects, classification accuracy using J48 Decision Tree obtained was 88.83%. Similarly, for value 2, classification accuracy was 89.28%, which was highest. For value 3, classification accuracy obtained was 87.50%. For value 4 and 5, the classification accuracy was 87.72%. For value 6, the classification accuracy was 86.83%. This was how, value of minimum number of object was varied till value 30. The graph was plotted for the above classification accuracy percentage value vs. minimum number of objects. The result was shown in Figure 11. As minimum number of object had given highest classification accuracy value (89.28%) hence, it was kept constant at value 2 and value of confidence factor was varied in the range of (0.05-1.00). For value 0.05, the classification accuracy of confidence factor, by using J48 Decision Tree algorithm was 88.88%.
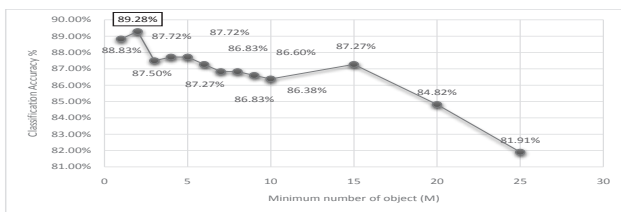
For value 0.10, 0.15 and 0.20 of confidence factor classification accuracy obtained was 89.06% respectively. For value 0.25 of confidence factor the classification accuracy obtained was more than all other confidence factor values *i.e.* 89.28%. After confidence factor value 0.25, classification accuracy remained constant at 89.28% for values (0.30-0.50) and then for confidence factor values 0.55 and 1 the classification accuracy was decreased again *i.e.* 89.06 %. The graph was plotted for the above classification accuracy percentage value vs. confidence factor. The result was shown in Figure 12. Selected parameters are minimum number of objects = 2 and confidence factor = 0.25, for selected seven features v1, v2, v3, v4, v5, v6, v10. With these conditions, highest classification accuracy was obtained *i.e.* 89.28%.

The stratified cross-validation summary is as follows:

Correctly Classified Instances	400	89.2857%
Incorrectly Classified Instances	48	10.7143 %
Kappa statistic		0.875
Mean absolute error		0.0385
Root mean squared error		0.1665
Relative absolute error		15.7326 %
Root relative squared error		47.5753 %
Total Number of Instances		448

The misperception matrix in the Table 2 designates the organization accuracy of the Decision Tree algorithm. The clarification of confusion matrix is as follows:

- Ordinal number of correctly classified instances is shown in diagonal elements of the misperception matrix.
- In the foremost row, out of 64 data points collectively, first element shows 57 number of data points that were classified as 'GOOD' class but misclassified as 1 data point to '10PF' class, 4 data points to '20 PF' class, 1 data point to '30PF' class and 1 data point to '100PF' class.
- In the second row, out of 64 data points collectively, second element shows 56 number of data points that
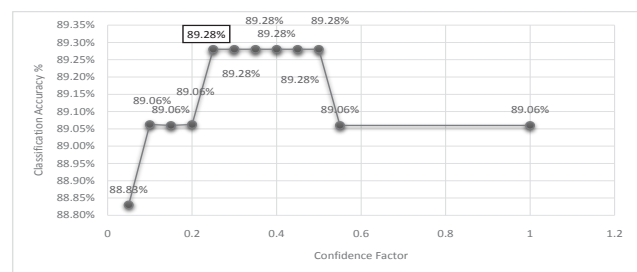

Figure 11. Minimum number of object vs. classification accuracy.

Figure 12. Confidence factor vs. classification accuracy.

Table 2. Confusion matrix of J48 Decision Tree

	GOOD	10PF	20PF	30PF	40PF	80PF	100PF
GOOD	**57**	1	4	1	0	0	1
10PF	1	**56**	2	2	0	2	1
20PF	0	12	**50**	2	0	0	0
30PF	2	0	3	**55**	3	2	1
40PF	1	0	1	2	**57**	0	3
80PF	0	0	1	0	0	**63**	0
100PF	0	1	0	1	0	0	**62**

Table 3. Detailed accuracy by class

Class	TP rate	FP rate	Precision	Recall	F-Measure	ROC area
Good	0.891	0.01	0.934	0.891	0.912	0.947
10 PF	0.875	0.036	0.8	0.875	0.836	0.937
20 PF	0.781	0.029	0.82	0.781	0.8	0.971
30 PF	0.859	0.021	0.873	0.859	0.866	0.93
40 PF	0.891	0.008	0.95	0.891	0.929	0.941
80 PF	0.984	0.005	0.969	0.984	0.977	0.99
100PF	0.969	0.016	0.912	0.969	0.939	0.976
Weighted average	0.893	0.018	0.894	0.893	0.893	0.956

were classified as '10PF' class but misclassified as 1 data point to 'GOOD' class, 2 data points to '20PF' class, 2 data points to '30PF' class, 2 data points to '80PF' class and 1 data point to '100PF' class.

- In the third row, out of 64 data points collectively, third element shows 50 number of data points that were confidential as '20PF' class but misclassified as 12 data points to '10PF' class and 2 data points to '30PF' class.
- In the fourth row, out of 64 data points together, fourth element shows 55 number of data points that were classified as '30PF' class but misclassified as 2 data points to 'GOOD' class, 3 data points to '20PF' class, 3 data points to '40PF' class, 2 data points to '80PF' class and 1 data point to '100PF' class.
- In the fifth row, out of 64 data points collectively, fifth element shows 57 number of data points that were classified as '40PF' class but misclassified as 1 data point to 'GOOD' class, 1 data point to '20PF' class, 2 data points to '30PF' class and 3 data points to '100PF' class.
- In the sixth row, out of 64 data points collectively, sixth element shows 63 number of data points that were confidential as '80PF' class but misclassified as 1 data point to '20PF' class.
- In the seventh row, out of 64 data points together, seventh element demonstrations 62 number of data points that were classified as '100PF' class but misclassified as 1 data point to '20PF' class and 1 data point to '30PF' class.
- Now, faulty circumstances are clearly different from 10% fault condition by algorithm. Other misclassification of faulty condition are offered in non–diagonal components. Here out of 448 data points, 48 data points were misclassified by algorithm. Error of about 10% is present, which is satisfactory for practical applications. Category-wise detailed accuracy of J48 algorithm is given in Table 3. 'TP rate' and 'FP' rate

are very significant. TP stands for True Positive and its value should be close to 1 for better classification accuracy. FP stands for False Positive and its value should be close to 0 for better classification accuracy. The both models confirm that build model is a good one.

8. Conclusion

In industrial machinery, gears play a really important part which is submitted to several flaws such as wear and tear, misalignment etc. In this composition, gear conditions evaluation is performed along the footing of the algorithm which is further based on extracted wavelet features. The Decision Tree algorithm was used for classification of condition of the gear. The feature extraction of vibration signals was performed by using wavelet energy. The model was tested with 10-fold cross validation method and hence good accuracy was attained. At the final stage, the result indicates that the Decision Tree model can be applied for diagnosing condition of helical gearbox using wavelet features.

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