ISSN (Print) : 0974-6846
Indian Journal of Science and Technology, Vol 9(33), DOI: 10.17485/ijst/2016/v9i33/101335, September 2016 ISSN (Online) : 0974-5645

Acoustic Signal Based Condition Monitoring of Gearbox using Wavelets and Decision Tree Classifier

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Abstract

Objectives: Most machineries employ gears for efficient power transmission. Even minor faults with the gear box can lead to severe losses both in terms of energy and money. The vibration and acoustic signals from the gear box, which usually are said to be as an unwanted by-product of the operation, can be used for the condition monitoring and fault diagnosis of the gearbox. This study proposes the usage of machine learning algorithm for condition monitoring of a helical gearbox by using the sound signals produced by the gearbox. **Methods/Analysis:** The acoustic signals were captured using microphone from a gearbox with artificially created fault conditions. An exhaustive study using different discrete wavelet transformations for feature extraction from the acoustic signals was carried out and subsequently J48 Decision Tree algorithm was employed for selection and classification of the extracted features. **Findings:** The time domain acoustic signals were converted into frequency time domain data using different discrete wavelet transforms. Of all the wavelet ransforms, the Daubechies 5 Discrete Wavelet Transform was found to be the best suited for the current scenario. The methodology yielded a satisfactory classification accuracy of 97.6% when classified using J48 algorithm. **Novelty/ Improvements:** The classification accuracy yielded through this methodology is higher than what was obtained by similar experiments with different methodologies till date. The results and their analysis is discussed in the study. The whole methodology when put in a real time sytem will have the capability to monitor the condition and diagnose the faults in the gearbox quickly and effectively. The performance of this methodology may be further improved by using different classifier algorithms.

Keywords: Acoustic Signal, Condition Monitoring, Decision Tree Classifier, Gearbox, Wavelets

1. Introduction

Gears are employed in almost all machineries for the continuous transmission of power. These machineries usually have multiple gears contained in the gearbox permitting power transmission at different speeds and loads. All the load during the transmission is taken by the gear tooth which means the failure of a single gear tooth may lead to reduction in efficiency of the power transmission or even the complete disruption of the same. Hence, it is of prime importance to ensure that the gearbox is running without any faults which can be achieved by using a real time condition monitoring system. The faults may have catastrophic effect in precision gearboxes with close tolerances, as a broken gear tooth may abruptly stop the rotation of the gear, thereby seriously damaging the gearbox itself and the machinery connected to it. As the gears are usually enclosed in the gearbox, the easy method by which the condition can be monitored is through the sound and vibration signals emitted from the gearbox. This study is aimed at reducing the chances of gearbox failures by real time condition monitoring through acoustic signals thereby preventing any mishaps by gear failures.

For this study, acoustic signals were preferred considering the cost of condition monitoring equipment. For

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vibration signals, accelerometers with high frequency response would be required which are too costly compared to the microphone used for sound signal recording. Several types of faults may occur in a gearbox and several factors may contribute to the same[1]. One of the common fault being gear tooth breakage, different levels of the same are artificially created on gear teeth and the acoustic signals for different fault levels and load conditions are recorded. These acoustic signals are believed to provide reliable data on different fault conditions that machine learning algorithms may be employed for early detection of faults in a real system[2]. This will allow for the better maintenance of the gearbox which translates into reliable and efficient power transmission.

The fault diagnosis is usually carried out by feature extraction, feature selection and feature classification. The commonly used feature extraction techniques are statistical features[3], histogram features[4] and wavelet features[5]. In this study wavelet features are used. FFT based signal processing techniques are found not to be useful for non-stationary signals like those from the gear box[6]. Even the STFT introduced to overcome disadvantages of FFT suffers from problems like window based analysis[7]. The wavelet transform is able to provide with the useful information about the signal for the fault identification[8]. The Continuous Wavelet Transform (CWT) was used in for gear and bearing fault diagnosis[9]. Though CWT provides useful information about the faults, it is not suitable for real time fault diagnosis because of the higher computation time required. In used Discrete Wavelet Transform (DWT) for fault diagnostics in induction machines and found to produce good results[10]. In used DWT and Zhao-Atlas-Marks (ZAM) distribution for spur gear fault diagnosis with vibration signals. In conducted a study on the same helical gear box via vibration and acoustic signals using Empirical Mode Decomposition; but, using statistical features.

The most common techniques for feature selection are fuzzy[11], Artificial Neural Network (ANN)[12], Decision Tree (DT)[13], Principal Component Analysis (PCA)[14], Genetic Algorithm (GA)[15], etc. Due to the compactness and ability to select best features easily, J48 Decision Tree was used in this study for feature selection.

For feature classification, most commonly used classifiers are Support Vector Machine (SVM)[16], Proximal Support Vector Machine (PSVM)[17], Artificial Neural Network (ANN)[18] and [19], Fuzzy, Decision Tree (DT)[20], etc. In developed a fault classification model for spur bevel gear box using Support Vector Machine and Proximal Support Vector Machines. The SVM based models suffer from higher training time and computational complexity when the number of patterns increases. In used DWT with ANN for fault diagnosis of bevel gear box. Though Artificial Neural Network classifier is very good result in most cases, training of an Artificial Neural Networks classifier was complex and time consuming process. For a real time system, the classifier used should consume least time with high classification accuracy. Therefore J48 Decision Tree algorithm was used for feature classification.

The fault conditions were simulated for 20%, 40%, 60%, 80% part of tooth chipped conditions and with a full tooth missing (100%) and half of another tooth (150%) chipped conditions, all at full load capacity of the machinery. A set of wavelet features were extracted using db5 wavelet and feature selection and classification were done using J48 Decision Tree. It was trained and the results were analysed.

2. Experimental Studies

2.1 Experimental Setup

The experimental setup consists of a 5.5 hp, 3 phase induction motor connected to a two stage gelical gearbox. The speed of motor is controlled by an inverter drive, and is set to 80 rpm. The gear ratio being 1:15, the second stage pinion shaft, which is connected to a DC motor, rotates at 1200 rpm. The specifications of the gearbox are as given in Table 1. The DC motor works as a generator to produce 2 kW which is dissipated to the resistor bank connected to it. This electrical setup is made in order to avoid the tortional vibrations which may occur if traditional dynamometers are connected. The backlash is ensured to be restricted only to the gears, by fitting tyre couplings between the gearbox and the motor. The whole setup is mounted on I-beams anchored to a heavy concrete block to reduce the vibration of the setup. A piezo-electric accelerometer B&K 4332 is stud-mounted to measure the vibration signals generated on the bearing housing of pinion shaft and its output is conditioned using B&K 2626 charge amplifier. As the placement of microphone is very important in this experiment, different positions and directions are tried out and found to produce good reception when kept at a distance of 55 mm near the pinion. The experimental setup is given by Figure 1.

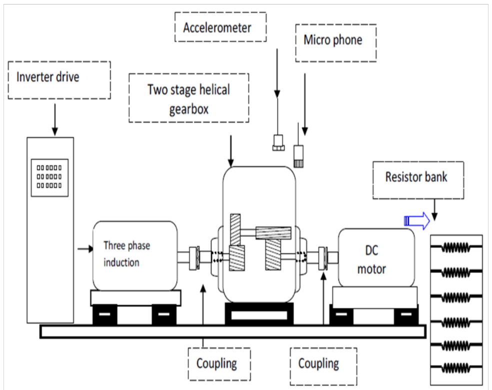

Figure 1. Experimental setup of two stage helical gearbox.

Table 1. Specifications of helical gearbox

	First stage	Second stage
Number of teeth	43/13	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	15	
Power transmitted	5 HP	

2.2 Experimental Procedure

Local faults in a gear box can beclassified into three categories. 1. Surface wear spalling[21], 2. Cracked tooth and 3. Loss of a part of tooth due to breakage of tooth at root or at a point on working tip (broken tooth or chipped tooth), of which, damage due to teeth breakage is very common in industries. The depth wise damage is simulated on the helical gearbox by partial tooth removal by grinding operation. A total of seven conditions are created by 0%, 20%, 40%, 60%, 80%, 100% and 150% tooth removal across the tooth width. The motor is run at 80 rpm and the acoustic signals are carefully recorded with microphone after proper signal conditioning. The recorded data is then extracted for features using MATLAB. Then the extracted features are classified using Weka 3.6 for finding the classification when using different classifiers.

3. Feature Extraction

The fault diagnosis was performed using the acoustic signal recorded from the gearbox using the microphone. The acoustic time-domain signal is converted into time-frequency-domain data by using Discrete Wavelet Transform (DWT) through wavelet decomposition. The wavelet decomposition results in the trend and details. Thus obtained trends is again decomposed into next level trend and details. The same methodology is repeated for multiple levels of trends to give multiple levels of details. For the current study, a signal length of is 2048 (2^{11}) is chosen and therefore, the signals can be decomposed into 11 levels. At each level, the detail co-efficient were used to compute energy content using the following formula.

$$Vi = \sum_{i=1}^{n} Xi2$$

Where $x_{i\,=}$ details coefficients.

n = number of details coefficients.

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

$V= (V_1, V_2, V_3, \ldots\ldots\ldots, Vm)$

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

$V_1, V_2, V_3 \ldots$ are energy content at given level

The following discrete wavelet transformations were used in this study.

1. Biorthogonal wavelet: bior – 1.1, 1.3, 1.5, 2.2, 2.4, 2.6, 2.8, 3.1, 3.3, 3.5, 3.7, 3.9, 4.4, 5.5, 6.8
2. Reverse biorthogonal: rbio – 1.1, 1.3, 1.5, 2.2, 2.4, 2.6, 2.8, 3.1, 3.3, 3.5, 3.7, 3.9, 4.4, 5.5, 6.8
3. Coiflet : coif – 1, 2, 3, 4, 5
4. Daubechies wavelet : db – 1, 2, 3, 4, 5, 6, 7, 8, 9, 10
5. Sym wavelet : sym – 2, 3, 4, 5, 6, 7, 8
6. Haar
7. Discrete Meyer : dmey

4. Wavelet Selection

The time domain signal was processed using 54 different discrete wavelet transforms from the seven wavelet families mentioned above. The extracted features from each of the wavelet transform is then fed into J48 algoritm to find the maximum classification accuracy resulted Figure 2 to Figure 7. Of all the DWTs mentioned, features extracted using Daubechies 5 gave the best classification accuracy when used with J48 Decision Tree and hence it is selected for the subsequent operations. Daubechies wavelet, represented as 'db n' is a family of orthogonal wavelets characterised by highest number of vanishing points (n) for a given support width of 2^{n-1} . Of the 2^{n-1} possible solutions for the point and orthogonality conditions, the solution whose scaling filter is producing the maximum phase is selected as the result.

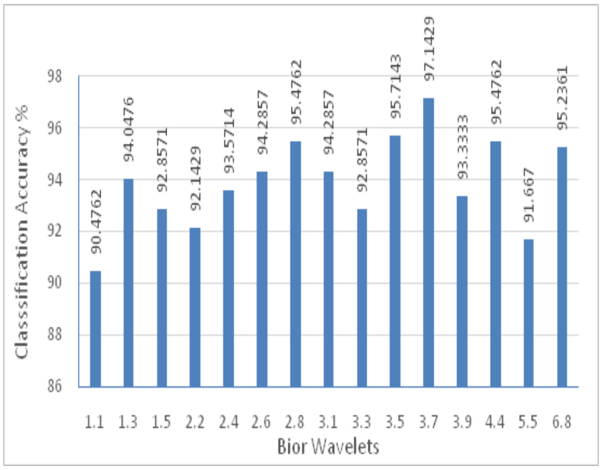

Figure 2. Classifiacation accuracy of bior wavelets.

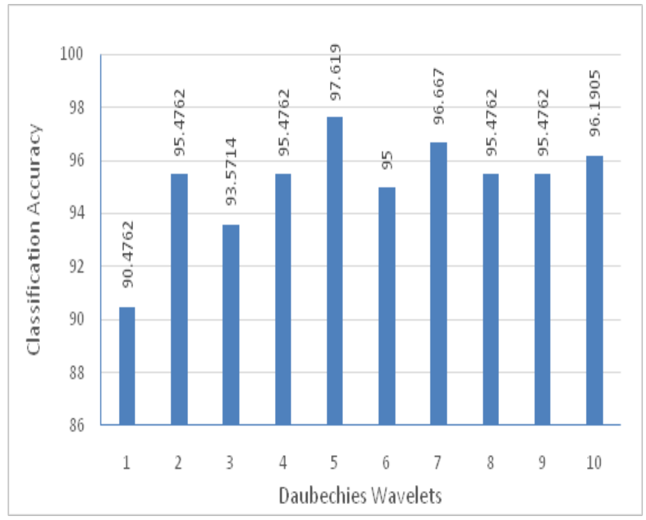

Figure 4. Classifiacation accuracy of Daubechies wavelets.

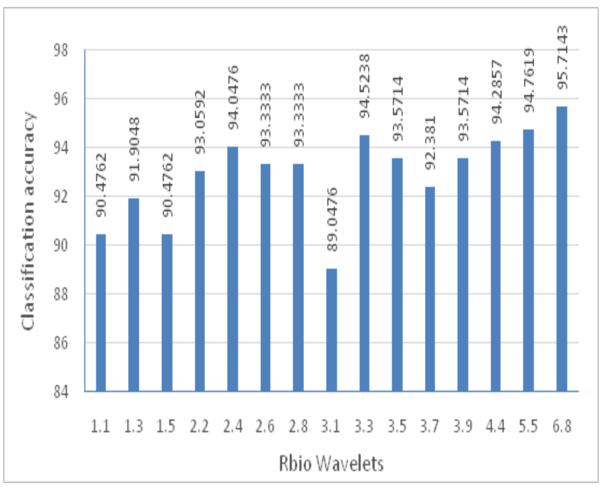

Figure 3. Classifiacation accuracy of rbio wavelets.

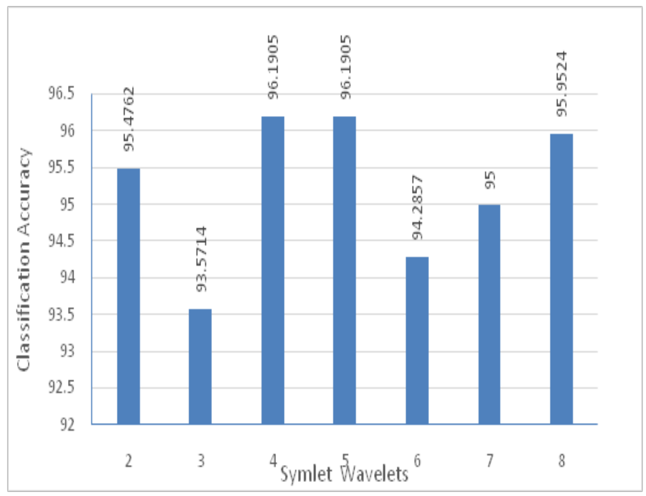

Figure 5. Classifiacation accuracy of Symlet wavelets.

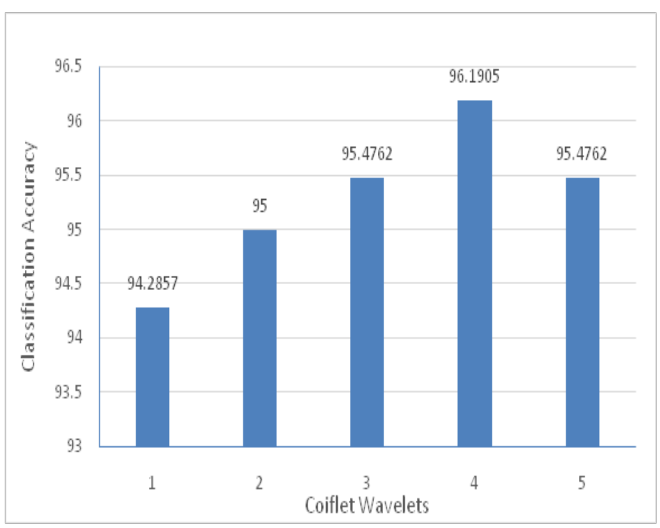

Figure 6. Classifiacation accuracy of coiflet wavelets.

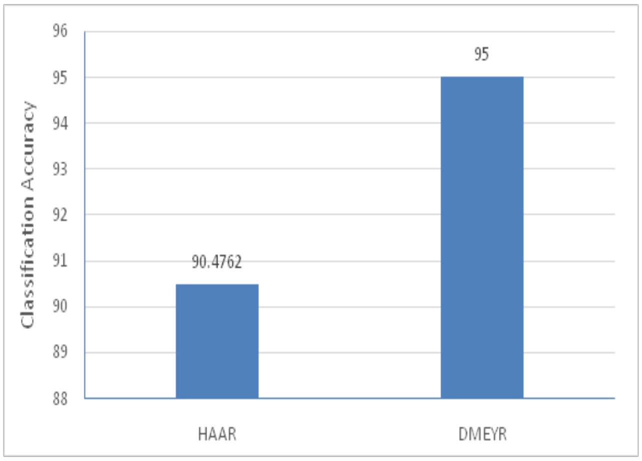

Figure 7. Classifiacation accuracy of Haar and dmeyr wavelets.

5. Feature Selection

The features extracted using Daubecies 5 wavelet transform is classified using J48 Decision Tree. The features which contribute most to the classification is found from the Decision Tree. The root node is the one on top of the Decision Tree and contribute most to the classification (i.e. V_2). The contribution of the features reduce down the levels. The number of features contributing to the classification accuracy is varied according to their priority in the Decision Tree. A maximum classification accuracy is obtained when the features V_1, V_2, V_3, V_4, V_5 and V_6 were used. Including the remaining features for classification showed no increase in accuracy. Therefore these features were removed and only the features those contributed for feature classification(V_1 to V_6) were selected for further processing.

6. Feature Classification

J48 is one of the most commonly used Decision Tree algorithm. This tree based knowledge representation methodology consists of branches, root, nodes and leaves to define classification rules. J48 Decision Tree algorithm is charecterised by a building phase and a pruning phase. In the building phase, the Decision Tree is built using the concept of information theory. For the entire training set, the tree uses a single root node and with every partition, a new node is added to the Decision Tree. For a set of samples in a partition *S*, a test attribute *X* is selected for further partitioning the set into $S_1, S_2, \ldots, S_L$. New nodes for *S* are created which are added to the Decision Tree as children. The construction of Decision Tree depends on the test attribute *X*.

J48 uses entropy based information gain as the selection criteria. As per information theory, entropy is a measure of the uncertainty in a random variable. The expected reduction in entropy due to the partitioning of the examples according to the given feature gives the information gain. It is a measure of the capability of a given attribute to separate its training examples according to the target function.

Information gain (*S, A*) of a feature *A* relative to a collection of examples *S*, is defined as:

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

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

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

$$Entropy(S) = \sum_{i=1}^{c} -Pilog2Pi \qquad (2)$$

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 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 overtraining. Thus for better classification accuracy, the trees must be pruned to remove less reliable branches[22]. This is usually done by removing the features which contribute negligibly to the classification

7. Results and Discussion

The acoustic signals from the helical gearbox under good condition and different fault conditions (20%, 40%, 60%, 80%, 100% and 150%) were taken. Subsequently feature extraction, selection and classification were carried out using DWT and J48 Decision Tree classifier.

The acoustic signals were transformed using different wavelet families and their classification accuracy using J48 Decision Tree were compared Figure 8. 11 features were extracted from the acoustic signals using Daubechies 5 wavelet transform (V_1 to V_{11}) and these features were found to give the maximum classification accuracy among all the Discrete Wavelet Transforms used. Of these, the features which contribute for the feature classification were selected, using J48 Decision Tree.

The features V_1, V_2, V_3, V_4, V_5 and V_6 combined gave the maximum classification accuracy and were selected for training and testing Figure 9. Rest of the features were removed as they tend to reduce the accuracy of the classifier. Figure 10 shows the Decision Tree for the feature classification.

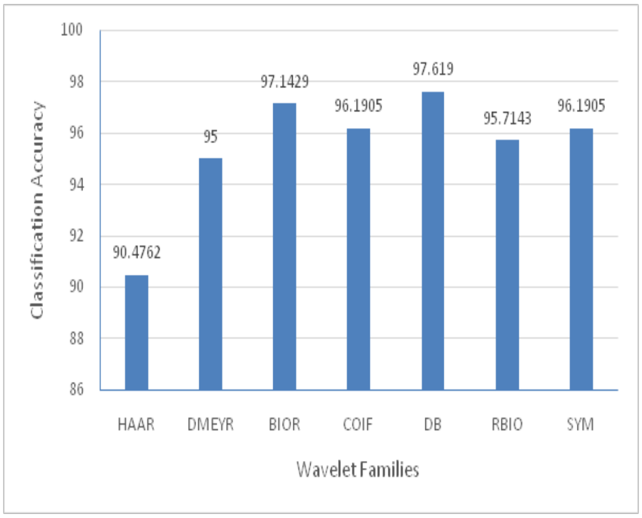

Figure 8. Classification accuracy of various wavelet families.

Figure 9. Effect of no. of features on classification accuracy.

7.1 Effect of Number of Features

- The Decision Tree Figure 10 gives a preview of the relative importance of the features extracted using db5 wavelet. The topmost feature in the tree contributes most to the classification (i.e. V_2), with the contribution reducing down the tree.
- The information gain by the reduction in entropy gives the measure of the discriminating capability of the feature in a given data set and thus useful features were selected.
- The classification accuracy with J48 is lower with less features and increases as the number of features increases, reaching a maximum value and thereafter it remains constant.

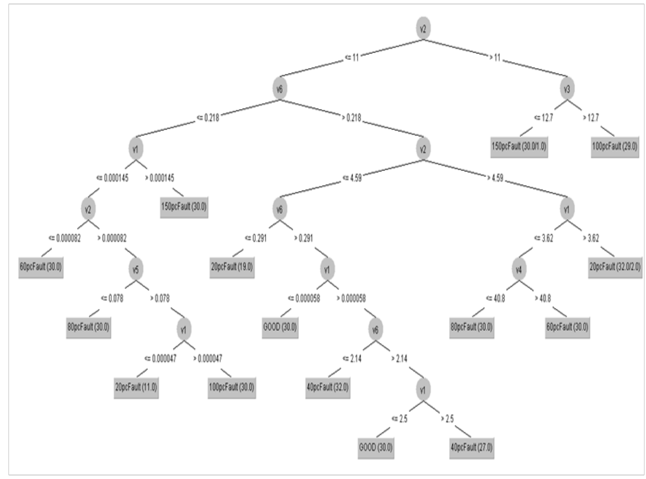

Figure 10. Decision Tree.

7.2 Feature Classification using J48 Decision Tree Algorithm

- Six features, V_1, V_2, V_3, V_4, V_5 and V_6, that have contributed for the classification were selected for training and testing from the J48 Decision Tree.
- As the number of instances increases, the classification accuracy first increases, gives a maximum accuracy when the number of random features or instances were 2 to 9, and thereafter decreases. The reduction in classification accuracy may be due to increase in complexity of the problem or unnecessary confusion when the number of features increases Figure 11.
-
- The best result with least computation time is shown when the number of instances was two.
- The classification accuracy showed no variations on varying other parameters of the J48 Decision Tree, such as confidence factor, number of folds or seeds.
- Table 2 shows the summary of stratified cross validation. The confusion matrix gives an insight into the misclassification. In confusion matrix the first row corresponds to the total number of data points for the "GOOD" condition of the gearbox, whereas,the first column in first

row corresponds to the correct classification as "GOOD" condition. In the current scenario all the data points in "GOOD" condition are classified as "GOOD" itself.

- The second row in the confusion matrix represents 20% fault condition and the first column represents misclassification of those data points as "GOOD" condition. The cell corresponding to the second row and second column in the confusion matrix represents the number of data points in 20% fault condition that have been correctly classified as 20% fault condition. In second row, one data point among 60 data is misclassified as "GOOD", one is misclassified as 150% fault and the rest are all correctly classified
- Similarly, from the confusion matrix, it can be inferred that 2 of the 60 in 40% fault were misclassified as 20% fault and the rest are correctly classified.
- The effect of misclassification become severe as in cases like the seventh row where one of the 150% faults is misclassified as a less severe 20% fault condition. However the overall classification accuracy is satisfactory as only 10 among the total 420 instances were misclassified.

Total Number of Instances 420
Correctly Classified Instances 410 97.619%
Incorrectly Classified Instances 102.381 %
Kappa statistic: 0.9722
Mean absolute error 0.0086
Root mean squared error 0.0822
Relative absolute error 3.5237 %
Root relative squared error 23.4897 %
Number of Leaves : 15
Size of the tree : 29
Time taken to build model: 0.01 seconds

The detailed summary of the classification of fearures from different classifications are given in Table 3. The True Positive (TP) rate is a direct measure of instances which are interpreted as true instances in the same class and ideally should be 1. In the case of class 'GOOD', all of the instances are classified correctly and therefore the TP rate is 1. The 20%, 40%, 100% and 150% classes are showing TP rate as 0.967 which is close to 1, which means that in most of the validations, the instances were correctly classified. Similarly, 60% and 80% fault classes have a better TP rate which shows most of the fulfilled conditions were interpreted as same. The False Positive (FP) rate is a measure of unfulfilled conditions interpreted as fulfilled conditions and for perfect classification, the FP

Table 2. Confusion matrix using J48 Decision Tree algorithm

	Good	20%Fault	40%Fault	60%Fault	80%Fault	100%Fault	150%Fault
Good	60	0	0	0	0	0	0
20%Fault	1	58	0	0	0	0	1
40%Fault	0	2	58	0	0	0	0
60%Fault	0	0	0	59	1	0	0
80%Fault	0	0	0	1	59	0	0
100%Fault	0	0	0	0	1	58	1
150%Fault	0	1	0	0	0	1	58

Table 3. Detailed summary

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
GOOD	1	0.003	0.984	1	0.992	0.999
20% Fault	0.967	0.008	0.951	0.967	0.959	0.98
40% Fault	0.967	0	1	0.967	0.983	0.99
60% Fault	0.983	0.003	0.983	0.983	0.983	0.99
80% Fault	0.983	0.006	0.967	0.983	0.975	0.989
100% Fault	0.967	0.003	0.983	0.967	0.975	0.981
150% Fault	0.967	0.006	0.967	0.967	0.967	0.979
Weighted Average	0.976	0.004	0.976	0.976	0.976	0.987

rate will be zero. From the table, it can be observed that, in all the classes, the FP rate is very close to zero. This is an indication of less number of Fault Positive conditions encountered during the classification. Precision is the fraction of the retrieved instances that are relavent while recall is the fraction of relevant instances that are retrieved and both should be ideally one. F-Measure is the mean of precision and recall. ROC area is the area under the curve in the plot of TP rate versus FP rate. Both F-measure and ROC Area will be one in perfect classification conditions.

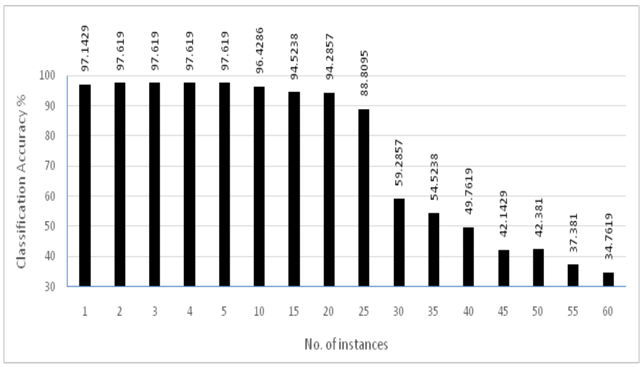

Figure 11. Change in J48 accuracy with no. of instances.

8. Conclusion

Discrete wavelet features extracted from the acoustic signals were used for classifying the gearbox faults. The J48 Decision Tree classifier was found give a satisfactory classification accuracy of 97.619%. The severity of misclassifications is found to be reasonably low. Hence, the proposed system which uses a combination of wavelet features with J48 Decision Tree classifier can be implemented effectively for the real time condition monitoring of the gearbox with a small expenditure for microphone and related components. This system can prove to be cost effective and can reduce chances of failure of gearboxes. This system will be able to predict the faults thus providing better maintenance and hence saving from machine downtime caused by breakdowns.

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