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Fault Diagnostics of a Gearbox via Acoustic Signal using Wavelet Features, J48 Decision Tree and Random Tree Classifier

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Abstract

Objectives: Heart of the transmission system in most machineries are gears for efficient power transmission. Even minor faults in gear can lead to major losses in terms of energy as well as in terms of money. The unwanted by-product while operating gear box are vibration and acoustic signals, which 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 acoustic signals produced by the gearbox. **Methods/Analysis:** The acoustic signals were captured using microphone from a gearbox with artificially created fault conditions. A comprehensive study was carried out using different discrete wavelet transformations for feature extraction which was further used in generating J48 decision tree algorithm and subsequently it was employed for selection and classification of the extracted features. **Finding:** Through this study the classification accuracy obtained is 97.619% by varying the different parameter to achieve the highest accuracy level. Data used in this study is exclusively obtained through experiment and subsequently through J48 decision tree and random tree classification accuracy level is studied to accomplish the highest accuracy. **Novelty/Improvements:** The comparison of different discrete wavelet transforms of the acoustic signals proved Daubechies 5 Discrete Wavelet Transform is the best suited one to use. The methodology yielded a satisfactory classification accuracy of 97.619%, which is higher than what was obtained by similar experiments with different methodology till date. The results and their analysis is discussed in the study. The performance of this methodology may be further improved by using different classifiers.

Keywords: Acoustic Signals, Gearbox, J48 Decision Tree, Random Tree, Wavelets

1. Introduction

Gearbox plays the most important role in the system of power transmission. Gearbox is the backbone in the field of dynamic world. Typical application of gearboxes are large in number, in electrical devices, automotive systems, ships, etc.

Monitoring the condition of gears while operating induces interest in recent years. It helps in cutting down the damage caused by failures of gear and to avoid unwanted downtime in industrial processes. Typically, vibrational signals cannot be detected while gears are engaged in operation, due to the low Signal to Noise Ratio (SNR) which enhances the chances of propagating a fault. Vibrations generated by large structural and noises often mask faults related to vibrational signals generated by smaller gears making it difficult to identify the fault related features[1]. Also, due to local faults in gear will show the transient effect in vibration and acoustic signals. In this study, acoustic signals are preferred over the vibration signals, since it is more economical to obtain, absence of physical contact and less time consuming. Acoustic signals can be analyzed by time frequency or time scale (wavelet) methods.

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The fault diagnosis is done by feature extraction, feature selection and feature classification. There are numerous techniques used for feature extraction such as statistical features[2], histogram features, wavelet features[3], etc. Fast Fourier Transform (FFT) is based on spectrum of signals due to low contact ratio. It's very difficult to detect the fault at its initial stage and also it is not useful for the non-stationary signals like in gearbox[4]. Short Time Fourier Transforms (STFT) is classical time frequency technique and some gear faults can be detected by inspecting the energy distribution of a signal over time frequency space[5]. The Continuous Wavelet Transform (CWT) is used by Rafiee et al. for gearbox diagnosis[6] it is useful in case of real time fault diagnosis despite producing good results of CWT is time consuming. In used Discrete Wavelet Transform (DWT) for fault diagnostics in induction machines and found to produce good results[7] similarly other transform are also available like Wavelet Packet Transform (WPT)[8]. This means recent advancement in Wavelet Transform (WT) provide as a very powerful tool for gear damage diagnosis. Wavelet Transform (WT) uses narrow time window for high frequencies and wide time window for low frequencies. It's is very effective for transient and non-stationary signals. Generally used technique for feature selection are Artificial Neural Network (ANN)[9,10], Fuzzy[11], Decision Tree (DT)[12], Principal Component Analysis (PCA)[13], Genetic Algorithm (GA)[14], etc. In this study J48 Decision Tree is used for the feature selection. In case of feature classification most common classifier which is generally used are Support Vector Machine (SVM)[15], Bayes Support Vector Machine (BSVM)[16], Proximal Support Vector Machine (PSVM)[17], Artificial Neural Network (ANN), In[18,19], Fuzzy, C4.5 Decision Tree (DT)[20], etc. In used DWT with ANN for fault diagnosis of bevel gear box. This whole study aims at reducing the time required for processing and enhancing the accuracy level. While using SVM, computational complexity increases when number of pattern is large in number. Artificial Neural Networking (ANN) and SVM classifier seems more complex and huge time consumable process.

In this study simulation of gear tooth is conducted with the help of gear box. Gears which went through simulation is in Good condition, 20%, 40%, 60%, 80%, 100% means full tooth missing, are defected condition gear and 150% defected condition which means one full tooth is chipped off and one half gear tooth is chipped off.

2. Experimental Setup and Procedure

The experimental setup is shown in Figure 1. The setup consists of a 5 HP two stage helical gearbox. The gear box is driven by a 5.5 HP, 3-phase induction motor with a speed of 1440 rpm. The speed is controlled by an inverter drive and for this study the motor is regulated at 80 rpm. At the end the speed of the first stage is 80 rpm, with a step-up ratio of 1:15, in the second stage the speed of the pinion shaft is 1200 rpm. Table 1 gives the outline of the specifications. The generated power by a DC motor is 2 kW to the pinion, which is spent in a resistor bank. Hence, the actual applied load on the gearbox is only 2.6 HP which is rated as 52% of its rated power 5 HP. In most of the industries, load varies from 50% to 100%. In the case of dynamometer, additional torsional vibrations can arises due to torque fluctuations. This is avoided in this case by using DC motor connected to a resistor bank for load.

Couplings are fitted between the electrical machines and gear box so that excess vibrations in the system can be restricted to the gears. The motor, gear box and generator are mounted on I-beams, which are most commonly used to attain a massive foundation. Vibration signals are measured using a Bruel and Kjaer accelerometer which is established close to the test bearing. Signals are sampled at a sampling frequency of 8.2 kHz. It is very problematic to study the fault detection procedures without fault trials. Local faults which are artificially generated in a gear box can be classified into three categories. 1. Loss of a part of tooth, 2. Surface wear and 3. Cracked tooth due to breakage of tooth at root or at a point on working tip (broken tooth or chipped tooth). There are different modes of methods to simulate faults in gears of gear box like Electric Discharge Machining (EDM), grinding and adding iron particles into a gearbox lubricant and over loading to the gear box i.e. accelerated test condition. The simplest approach to detect the fault is partial tooth removal. This simulates the partial tooth break, which is common in many industries[21–24].

3. Feature Extraction and Wavelet Selection

The signals that acquired in time domain can be used to perform fault diagnosis. Wavelet Transform (WT) has

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 **Rated power** **Power Transmitted**	1:15 5 HP 2.6 HP	

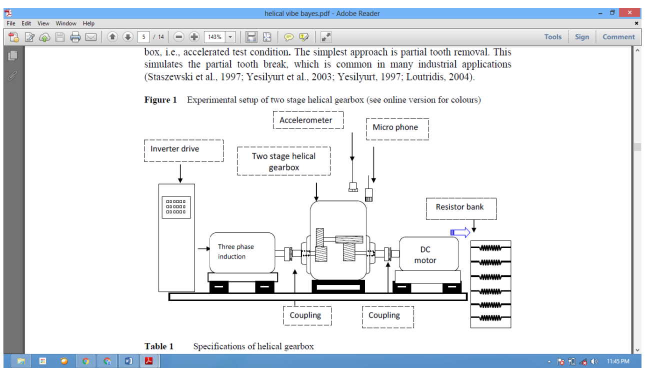

Figure 1. Experimental setup.

been widely used and provides the physical characteristics of time-frequency domain data. The details and trend are presented in the wavelet decomposition results. Thus the obtained trend and details is again decomposed into next level trend and details. The same method is followed for multiple levels of trends to give multiple levels of details. For the current study, a signal length of is 2048 (211) 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.

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

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,………,V_m).

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

V_1, V_2, V_3… are energy content at given level.

The following discrete wavelet transformations were used in this study:

- 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.
- 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.
- Coiflet: coif – 1, 2, 3, 4, 5.
- Daubechies wavelet :db – 1, 2, 3, 4, 5, 6, 7, 8, 9, 10.
- Sym wavelet : sym – 2, 3, 4, 5, 6, 7, 8.
- Haar.
- Discrete Meyer : dmey.

Daubechies wavelet gives more precisely (db5) when used with J48 Decision Tree. Daubechies wavelet, is known as ‘db m’ which is a family of orthogonal wavelets characterized by highest number of vanishing points (m) for a given support width of 2m-1. Of the 2m-1 possible solutions for the point and orthogonality conditions, the solution whose scaling filter is producing the maximum phase is selected as the result as shown in Figure 2.

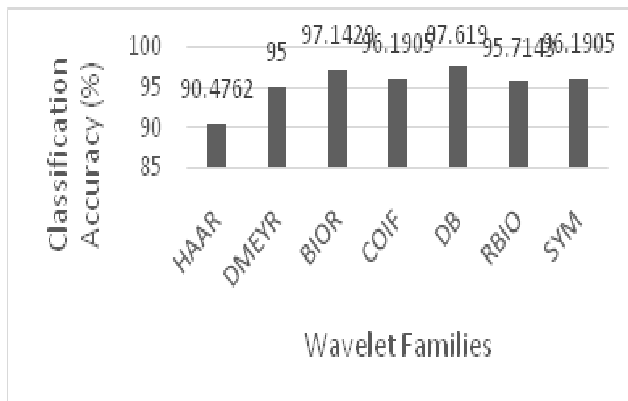

Figure 2. Classification accuracy of various wavelet families.

4. Feature Selection

J48 is an open source Java implementation of the C4.5 algorithm in the Weka data mining tool. C4.5 is a program that creates a Decision Tree based on a set of labeled input data. This algorithm was developed by Ross Quinlan. The Decision Trees generated by C4.5 can be used for classification and for this reason, C4.5 is often referred to as a statistical classifier.

In Weka, data mining tool, J48 algorithm is applied to build a Decision Tree and most of the node of the tree is divided into multiple subsets and division is done on the bases of Information Gain (IG) value that is basically the highest number of vanishing value. The Decision Tree is formed by using a J48 algorithm. Through which these attributes are selected.

For the entire training set the tree has a single root node. For every partition in Decision Tree a new node is added. For a set of samples in a partition S, a test attribute X is selected. Similarly, partitioning the set into S_1, S_2,. . ., S_L. New nodes for S are created which are added to the Decision Tree. The construction of Decision Tree directly depends on the test attribute X.

The selection criteria in J48, uses entropy based information gain. As per information, the uncertainty in a random variable is a measure of entropy. The information gain can be carried out by reducing entropy due to the partition. It is generally 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:

$$Gain(S,A) = Entropy(S) - \sum_{v \in Values(A)} \left(\frac{|S_v|}{|S|} \right) Entropy(S_v) \quad (2)$$

Where Sv = ({s ∈ S| A(s) = m}).

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

$$Entropy(S) = \sum_{i=1}^{c} -Pilog2Pi \quad (3)$$

Where ‘Pi’ is the proportion of ‘S’ belonging to the class ‘i’ and ‘c’ is the number of classes.

The second term in the above equation is the expected entropy after S is partitioned using feature A.

When the data is huge, the Decision Tree becomes large and more widely speeded which leads to more inaccuracy due to overtraining. Thus for better classification accuracy, the trees must be pruned to remove less reliable branches.

5. Feature Classification

There are various ways to classify the classification technique based on Statically Learning Theory (SLT). It uses support vectors to represent decision boundaries. For the fault detection of the data sets various machine based algorithm has already been developed.

- Random Tree: A random tree is a tree constructed randomly from a set of possible trees having *K* random features at each node. “At random” in this context means that in the set of trees each tree has an equal chance of being sampled. Trees have a “uniform” distribution. Random trees can be generated efficiently and the combination of large sets of random trees generally leads to accurate models. There has been an extensive research in the recent years over random trees in the field of machine learning.

For this model random tree algorithm has been used to achieve highest accuracy its various classifier parameters like

MinNum value – Minimum number of instances,

Depth - Maximum depth of the tree,

Seed - Randomly selecting attributes.

K value - Number of sets used for randomly chosen attributes.

For better classification Decision Tree should be compact and should not be complex, otherwise, it will reduce the accuracy level. While using random tree algorithm the parameters of this like depth, Seed Value and *k* value are varied to get the maximum accuracy possible. The maximum value of parameters were found by keeping one parameter constant and varying the other to get the highest accuracy value.

6. Result and Discussion

Acoustic signals from the gearbox were taken. Gears which were taken to do this study are in “GOOD” condition and different fault conditions (like 20%, 40%, 60%, 80%, 100%, 150%). Feature extraction has been done from the acoustic signals which was further followed through the features selection and later it was gone through the features classification. Subsequently feature extraction was carried out with the help of Wavelet Transform whereas feature selection was done by J48 decision tree as shown in Figure 3 and the classification is done by random tree classifier.

- 11 features are extracted from the acoustics signals using Daubechies-5 wavelet transform (v1-v11).
- Out of 11, the highest contribution of the features in features classification were selected using J48 decision tree that is v1, v2, v3, v4, v5 and v6.
- Decision Tree basically gives the overview of the contribution of a particular extracted fea-

ture using db5 wavelet transform. The topmost feature contributed most into the classification that is v2 and as we move down to the roots the contribution decreasing. The selected features (v1-v6) were used for training and testing Figure 4. Rest of the features were removed as they tend to decrease the accuracy of the classifier.

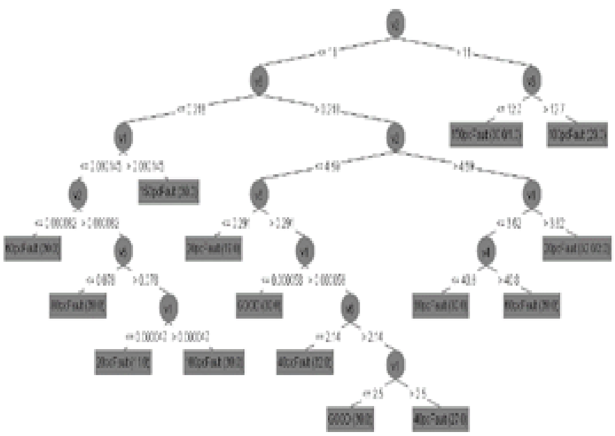

Figure 3. Decision Tree.

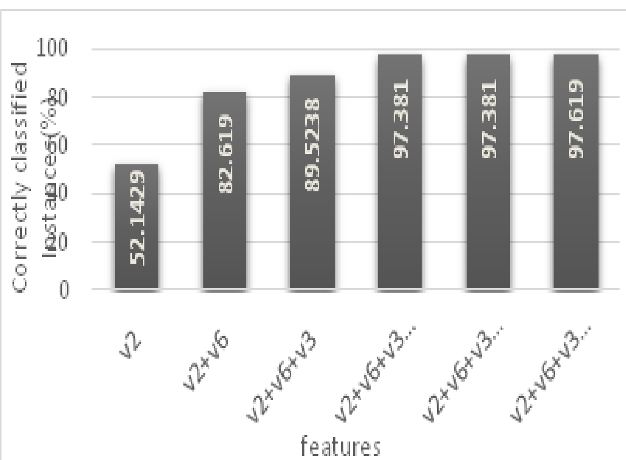

Figure 4. Correctly classification instances vs. features.

The classification accuracy with J48 is lower with less number of features and while increasing the number of features, classification accuracy increases.

- Classification of features were done by using random tree and its various parameter were changed like:
  - Depth - The maximum depth of the tree.
  - Seed - The random number seed used for selecting attributes.
  - *K* value - Sets the number of randomly chosen attributes.
  - minNum value - The minimum total weight of the instances in a leaf.

Various graphs were obtained from the feature classification by varying the various parameters. From Figure 5 obtained value of maximum correctly classification instances is 95.9524%. So the minimum weight of the instances is selected that is one.

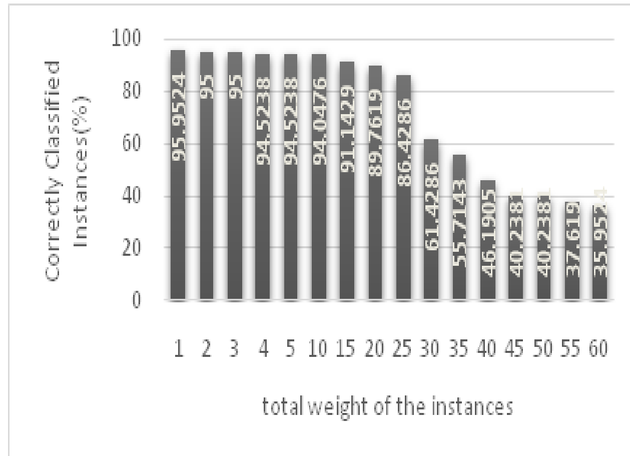

Figure 5. Classification of features vs. minimum number of instances.

After fixing minimum number of instances as one varying the randomly chosen attributes, a maximum accuracy of 97.381% achieved, when randomly chosen attributes is four as shown in Figure 6.

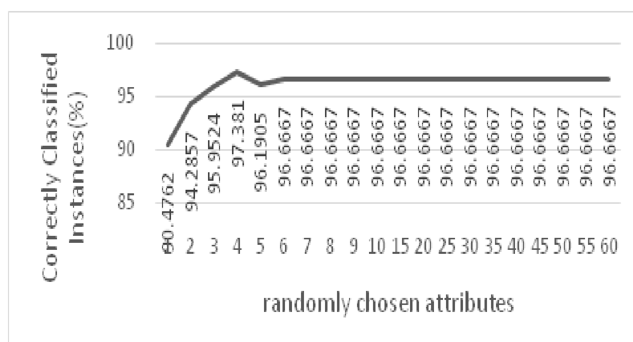

Figure 6. Classification of features vs. randomly chosen attributes.

Now, simply fixed the randomly chosen attributes value as four and minimum number of instances as one. Now vary the other parameter such as Seed Value that is randomly number of Seed used for selecting attributes and the obtained accuracy level is 97.619% as shown in Figure 7 which occur at when Seed Value is 15 and 50.

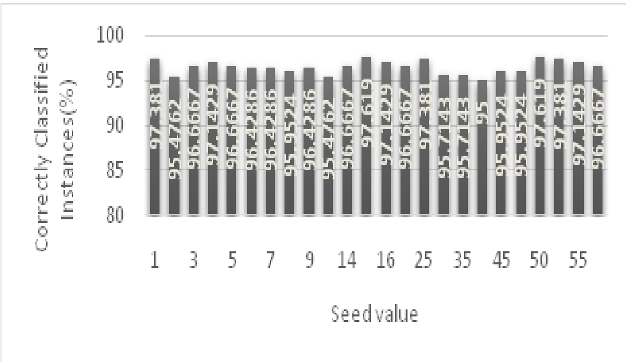

Figure 7. Classification of features vs. Seed Value.

To improve accuracy, all the parameters except depth is fixed, that is maximum depth of the tree, fixed minimum number of instances as one, randomly chosen attributes as four and then Seed Value as fifteen and fifty.

In Figure 8 the depth value is vary after fixing other parameter and Seed Value as fifteen, obtained the maximum accuracy at depth 0 and becomes constant after 8.

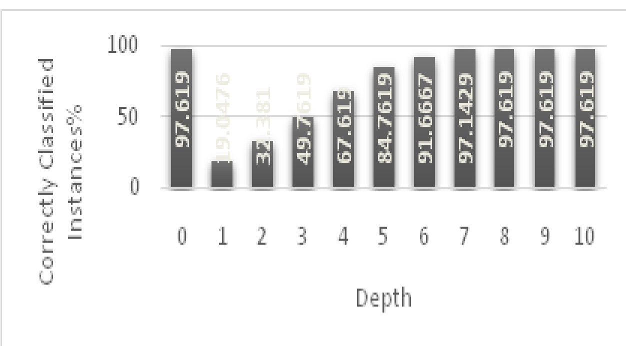

Figure 8. Classification of features vs. depth.

Similarly the depth value is vary after fixing the other parameter and this time the Seed Value is 50 which gives the maximum accuracy level as 97.619% as shown in Figure 9 at depth of 0 and it becomes constant after 6.

The summary of the depicted result is given:

Correctly classified instances: 97.619% (410)

Incorrectly classified instances: 2.381% (10)

Kappa statistic: 0.9722

Mean absolute error: 0.0068

Root means squared error: 0.0825

Relative absolute error: 2.7778%

Root relative squared error: 23.5702%

Total Number of Instances: 420

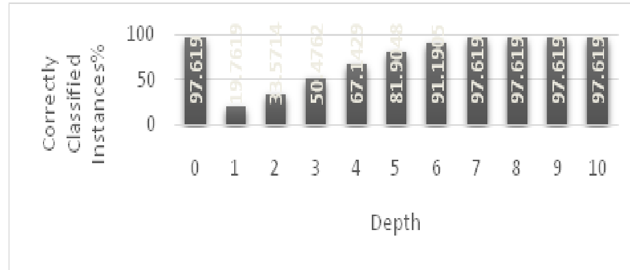

Figure 9. Classification of features vs. depth.

Subsequently following confusion matrix was obtained as shown in Table 2.

Table 2. Confusion matrix

Class - ified	Good	20% Fault	40% Fault	60% Fault	80% Fault	100% Fault	150% Fault
Good	**58**	0	0	0	2	0	0
20% Fault	0	**54**	2	2	1	0	1
40% Fault	0	0	**60**	0	0	0	0
60% Fault	0	0	0	**58**	2	0	0
80% Fault	0	1	1	0	**58**	0	0
100% Fault	0	0	0	0	0	**58**	2
150% Fault	0	0	1	0	0	2	**57**

According to the confusion matrix, the sample of 60 extracted feature of 'Good Gear', only 58 are classified as extracted feature of 'Good Gear' while other 2 are misclassified as '80% fault'. Similarly, for the next sample, out of 60 data points of 20% fault gears, only 54 are classified as 20% faulty, two are misclassified as 40% faulty, other two are misclassified as 60% faulty, 1 is misclassified as 80% faulty and the last one is misclassified under 150% faulty. Similarly, the next sample of 60 has been tested which is known as 40% faulty and all the 60 are classified as 40% faulty. Similarly other batches of sample has been classified. From the last sample of 60 that is 150% faulty gears, 57 are classified as 150% faulty gears. Although, one is misclassified as 40% faulty gear and two are misclassified as 100%. This shows that gear having 150% fault are counting into some other category which is a serious issue because in actual one and a half tooth is missing but after going through classification it is counted into 40% faulty that is only 20% tooth is missing. Similarly, two are misclassified as 100% fault which shows that two, full tooth are missing but in actual 150% fault of gear is present.

Table 3. Detailed summary

Class	TP Rate	FP Rate	Preci - sion	Recall	F-Measure	ROC Area
Good	0.983	0	1	0.983	0.922	0.922
20% Fault	0.967	0.006	0.967	0.967	0.967	0.981
40% Fault	0.983	0	1	0.983	0.992	0.992
60% Fault	0.967	0.006	0.967	0.967	0.967	0.981
80% Fault	0.983	0.008	0.952	0.983	0.967	0.988
100% Fault	0.967	0.003	0.983	0.967	0.975	0.982
150% Fault	0.983	0.006	0.967	0.983	0.975	0.989
Weig - hted Avg.	0.973	0.004	0.976	0.976	0.976	0.986

The detailed summary of the classification of extracted features from the acoustic signals are given in Table 3. The True Positive (TP) rate is basically a direct measure of instances which are understood as true instances in the same class and ideally it should be 1. Although, in case of 'Good', 40%, 80%, and 150% faulty classes are showing the TP rate as 0.983 which is close to 1 which means that in most of the cases, the instances were correctly classified and on the other hand 20%, 60% and 100% faulty classes having TP rate as 0.976 which is also close to 1. The False Positive (FP) rate is a measure of unfulfilled conditions, the FP rate will be zero. From the table, it can be observed that, in case of 'GOOD', 40% faulty classes have FP rate as 0 and rest of all the classes, the FP rate is very close to zero. This is an indication of less number of faults positive conditions were experienced during the classification. Precision is the fraction of the retrieved instances that are relevant while recall is the fraction of relevant instances that are retrieved and both should be ideally one. F-Measure is the average 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.

7. Conclusion

The features are extracted from acoustics signals through Wavelet Transform to detect the faults in gearbox. J48 algorithm is used for the feature selection. The maximum classification accuracy which is obtained while going through this process is found out to be 97.619%. Hence, the proposed system can be implemented in real time condition monitoring of a gear box which also works in non-stationary conditions. The efficiency of this proposed system is high and cost required for this processes is less. This system will be able to predict the faults thus providing better maintenance and hence saving from severe faults.

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