CONDITION MONITORING OF GEARBOX OF AN IC ENGINE USING VIBRATION ANALYSIS THROUGH SIGNAL PROCESSING AND MACHINE LEARNING TECHNIQUES

Thesis

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

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DEDICATION

This thesis is dedicated to:

- *My parents, wife and my entire family members, without whom this would not have been possible. Also dedicated to my dear daughter Klisha,*
- *My teachers who taught us the purpose of life,*
- *My friends who encouraged and supported me,*

*I dedicate this research work***.**

DECLARATION

I hereby *declare* that the Research Thesis entitled "**CONDITION MONITORING OF GEARBOX OF AN IC ENGINE USING VIBRATION ANALYSIS THROUGH SIGNAL PROCESSING AND MACHINE LEARNING TECHNIQUES**" which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfillment of the requirements for the award of the Degree of **Doctor of Philosophy** in **Department of Mechanical Engineering** is a *bonafide report of the research work carried out by me.* The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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CERTIFICATE

This is to *certify* that the Research Thesis entitled **"CONDITION MONITORING OF GEARBOX OF AN IC ENGINE USING VIBRATION ANALYSIS THROUGH SIGNAL PROCESSING AND MACHINE LEARNING TECHNIQUES"** submitted by **Mr. RAVIKUMAR K.N. (Register Number: 158007ME15F22)** as the record of the research work carried out by him, is *accepted as the Research Thesis submission* in partial fulfillment of the requirements for the award of degree of **Doctor of Philosophy.**

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(Ravikumar K.N.)

ABSTRACT

Fault diagnosis of the internal combustion engine gearbox is extremely important for enhancing the efficiency of the engine and preventing the failure of connected components. Bearings and gear elements are the primary components of a gearbox, which operate in a variety of dynamic conditions with varying load and speed. Because of these severe operating circumstances, gear tooth and bearing problems occur in gearbox parts. If these flaws are not addressed, the result is a catastrophic breakdown of the gearbox, which is extremely costly and also causes additional risks in the industry. Monitoring the state of the gearbox while the engine is operating is critical to preventing damage to the other components of the engine, which is extremely useful in order to minimize component loss. As a result, it is important to select an effective and efficient technique for monitoring gearbox health without interfering the engine running.

This research focuses on the condition monitoring of an engine gearbox utilizing vibration signals with signal processing and artificial intelligence approaches. The gearbox is investigated in both healthy and simulated defective conditions, such as gear tooth damage and bearing defects, which occur mostly during operation. The vibration signals from the gearbox are collected in both healthy and defective conditions and these signals are then analyzed to determine the state of the gear and bearing. The current research work is divided into two stages.

The initial part of the work involves identifying/detection of gearbox conditions by analyzing vibration signals using basic signal processing techniques. To identify gearbox conditions, signal processing methods such as time-domain analysis, frequency domain analysis, time-frequency domain analysis, cepstrum analysis and wavelet analysis are used. Employing vibration signals, frequency domain analysis gave significant information on the gearbox condition. Even while signal processing methods give diagnostic information. Assessing the signals needs expertise in the area and these approaches are not suitable for studying nonstationary signals. Machine learning/deep learning is one of the best alternatives for building an effective condition monitoring system for developing an autonomous fault detection system for gearboxes based on artificial intelligence technologies.

In the second phase, artificial intelligence models are used to investigate gearbox conditions based on vibration signals. Machine learning approaches are divided into three stages: feature extraction, feature selection and feature classification. Statistical features, empirical mode decomposition (EMD) features and discrete wavelet transform (DWT) features are extracted from the vibration signals. These extracted features are given as input to the decision tree-J48 algorithm for selecting significant features. The classifiers such as support vector machine (SVM), K-star random forest are used to classify the conditions of gearbox elements using selected features. Fault diagnosis using vibration signals are carried out by making use of different set of features and classifiers with selected features from the decision tree technique. The drawback of manual feature extraction method is time consuming, laborious, requires expertise to understand the features for different set of signals. To address these issues, deep learning techniques such as convolution neural network (CNN), residual learning, softmax classifier and long short-term method (LSTM) are used to develop an automatic feature extraction method for fault diagnosis of gearbox.

Outcome of the machine learning techniques showed that, vibration signal-based fault diagnosis provided better classification accuracy in classifying the gearbox conditions. Present research work has demonstrated that discrete wavelet features served as best features among all other features such as statistical and EMD features. It was also observed that K-star algorithm provided better classification accuracy in comparison to other classifiers such as SVM and random forest algorithm. Also, results obtained from deep learning techniques provided promising classification accuracy by adopting automatic feature extraction techniques such as CNN, residual learning and stacked LSTM algorithm. Based on the research work, it is proposed that the combination of wavelet feature with K-star algorithm as a classifier is the best feature-classifier pair for diagnosis of gearbox conditions using vibration signals.

Keywords: Condition monitoring, Gearbox, IC engine, Vibration analysis, Signal processing techniques, Machine learning techniques, Deep learning technique

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ABBREVIATIONS

IC	Internal Combustion
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
EMD	Empirical Mode Decomposition
FFT	Fast Fourier Transform
ML	Machine Learning
DM	Data Mining
DT	Decision tree
GB	Gearbox
FRFT	Fractal Fourier Transform
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
ANN	Artificial Neural Networks
SVM	Support Vector Machine
RF	Random Forest
HT	Hilbert Transform
CM	Condition Monitoring
DL	Deep Learning
CNN	Convolutional Neural Network
BN	Batch Normalization
BP	Back Propagation
LSTM	Long Short-Term Memory
SGD	Stochastic Gradient Descent
RNN	Recurrent Neural Network
STFT	Short Time Fourier Transform
KNN	K Nearest Neighbor
WPT	Wavelet Packet Transform

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Internal combustion (IC) engine is an essential component required to power any automobile. The IC engine is composed of several systems and components, including a piston, a crankshaft, a connecting rod, gears and bearings. Each component in the engine contributes significantly to the engine smooth operation and it is essential to keep all components in good condition for optimal performance. It is necessary to check engine parameters regularly to minimize downtime caused by engine component failure.

The gearbox of an IC engine is a critical component of every automobile. It is the component responsible for transmitting power from the driving end to the non-driving end (Peng et al. 2016). It is important to examine the state of the engine gearbox on a regular basis in order to avoid failure of the complete system and to decrease the chances of engine breakdown. Therefore, it is important to identify defects in these critical machine parts at the earliest possible stage of their deterioration.

Condition monitoring (CM) is the practice of monitoring a machine condition parameter in such a way that any substantial change indicates the onset of failure. It is a critical component of the approach of predictive maintenance. Vibration-based monitoring methods have gained substantial momentum in the investigation and diagnosis of rotating machine components in recent years. Vibration occurs in machines as a result of cyclic excitation forces generated by component misalignment, imbalance, wear, or failure (Rao and Yap 2011). There are several machine components that operate under various loading conditions on any machine or equipment. IC engines, wind tunnels, airplanes, thermal power plants, pumps, generators, gas turbines and compressors are just a few examples of systems that are subjected to a range of loads under a wide range of operating conditions. CM of individual IC engine components is necessary for avoiding failure and minimizing engine downtime in a plant by detecting engine component problems using vibration signature analysis. In this work, a twowheeler motorcycle engine is used to diagnose faults in four-stroke IC engine gearbox components using vibration signals. Individual component condition is monitored and detailed analysis of these rotating components of an IC engine is performed using vibration analysis to avoid severe damage to the engine and other connected components.

1.2 IMPORTANCE OF MONITORING AN IC ENGINE GEARBOX

In an IC engine or any machine, a very small defect can lead to a reduction in the expected lifetime of a highly expensive engine. Industries or manufacturers must prevent these avoidable losses. These minor defects not only reduce the engine performance, but they can also result in the failure of another component. If these small defects are neglected, they can result in severe financial loss for the firm or even personal injury. Machine condition monitoring is necessary because the information collected through monitoring techniques may be used to determine the health of the machine. This information may be utilized as warning signs for the scheduled maintenance plan and by using these techniques, maintenance or repair costs will be reduced.

Progressive tooth wear and surface bearing defects are the most common causes of gearbox failure in IC engines, which have a severe influence on the engine performance and efficiency. As a result, it is essential that gearbox components do not degrade to the point of causing harm to other gearbox components. Hence, it is important to recognize/diagnose the gearbox condition utilizing a condition monitoring system while the engine is operating. The next section will discuss the different methods of monitoring the condition of a gearbox.

1.3 TYPES OF CONDITION MONITORING TECHNIQUES

In general condition monitoring techniques are classified in to two major categories, (Prabhu and Sekhar 2008) as follows,

1.3.1 Signal based methods

In the fault detection process, the primary goal of signal processing methods is to distinguish between faulty and fault-free instances from the system response signals. This is achieved without the need of a mathematical model. Measured signals can be analyzed in three ways: (i) frequency domain, (ii) time domain and (iii) time–frequency domain, according to signal processing methods. CM systems involves two types of measuring systems namely, direct measurement and indirect measurement.

Currently, indirect measurements are more suitable for online monitoring of IC engine gearbox. Indirect measurements are based on the relationship between the measuring data of the engine and the health conditions. The measuring data, such as vibration signals, temperature signals, sound signals, lubrication oil analysis, acoustic emission (AE) signals, etc. are acquired using particular sensors such as accelerometer, temperature sensor, microphone, oil samples, acoustic sensor, etc.

1.3.2 Model based methods

A model-based approach is based on the concept of analytical redundancy and is based on the comparison of system wide available measurements with prior information represented by the mathematical model of the system. New model-based fault diagnosis techniques are developed to meet the demand for increasingly intelligent CM systems for the maintenance of modern industrial process. Analytical models can be very useful to study the effects of gear tooth geometry on the various parameters, but these models are too complex to be of any value in a real-time CM system. The non-linear, stochastic and time invariant nature of mechanical systems makes modelling very difficult. A transformation between the signal characteristics and the physical system representing the process is necessary to establish such a model. Because of the complexity of the engine, modelling of the physical system cannot be achieved analytically in most cases.

1.4 METHODS OF CONDITION MONITORING

Sensor/transducer is a term that refers to a device that transforms one type of energy to another type of energy. It processes a physical quantity of the system under study in such a way that it generates a signal that can be read easily by an instrument or an observer. During operation, mechanical systems generate a variety of energy types, including radiant energy, thermal energy, electrical energy and mechanical energy.

The input quantities or properties that are to be measured by sensors are called measurands. The common measurands for mechanical system monitoring are as shown in Figure 1.1.

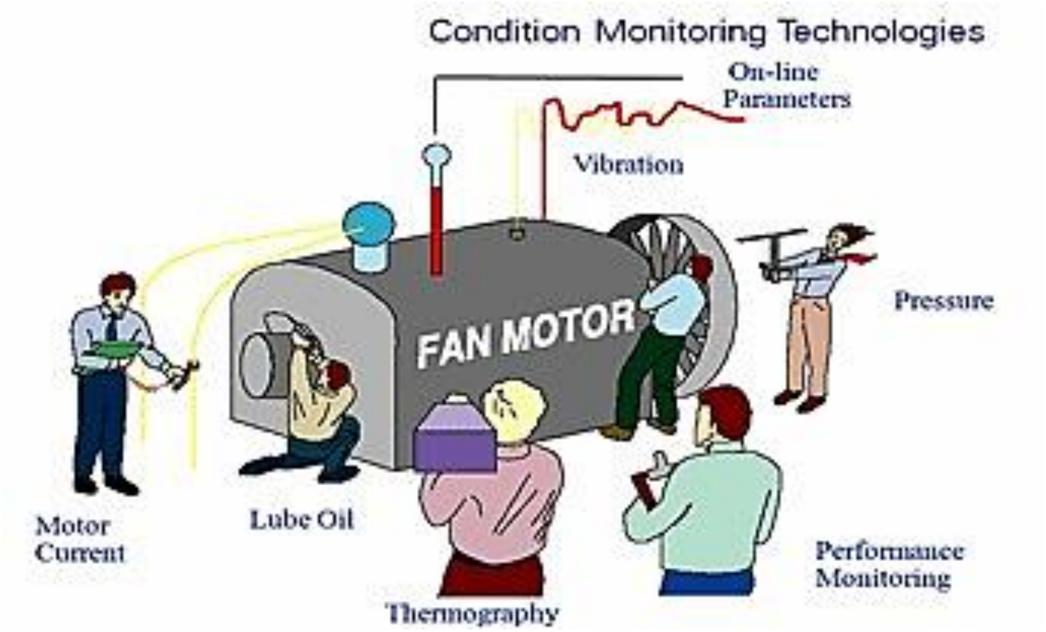


Figure 1.1 A variety of condition monitoring technologies (Courtesy: NI instruments)

In general, six types of sensor signals are most widely used to monitor the mechanical system i.e., vibration signals, pressure signals, motor power/current signals, lubrication oil analysis, temperature analysis, sound signals, acoustic emission signals and performance monitoring. In condition monitoring predominantly used techniques for fault detection in machines/structures (Scheffer and Girdhar 2004); are as follows,

(a) Visual inspection

This method is one of the very basic forms of monitoring technique which requires a technically skilled person to interpret the machines visually by hearing sound or observing amplitude of vibration induced in the defective machines.

(b) Performance monitoring

Performance monitoring is one of the traditional methods of monitoring production equipment which relies on visual inspection and physical senses to determine whether a piece of machinery is operating properly or not. Additionally, in this method, output and manufacturing performance of a machine is tracked to identify deviations from expected results. When production output changes, defects increase, or physical characteristics (heat, sound, vibration) deviate noticeably from the normal trend, which may indicate equipment problems and possible failures. Indicative performance parameters are examined to reveal the machine operating performance. This is used to determine the performance problems in equipment. The efficiency of machines provides a good insight on their internal conditions.

(c) Thermography

Thermography is a non-destructive testing technology for detecting and quantifying minute temperature changes in order to assist in the detection of asset and plant site deterioration. This is used to detect thermal or mechanical defects in oil refineries, steel industries, power plants, boilers, overhead lines, generators, misaligned coupling, transformers and cell damage in carbon fiber structures on aircrafts. Thermal energy is emitted by objects that are invisible to the naked eye. An infrared camera can detect thermal energy and map the object's temperature changes. The recorded picture depicts the movement of heat flow to, from and/or through an object. Temperature differentials can reveal a variety of issues, including corrosion and erosion, insufficient insulation and defects in materials or structures, such as holes or inclusions.

(d) Lubricating oil analysis

Lubricating oil is analyzed to detect micro particles of wear debris of bearing and gear due to direct contact with the lubricating oil film. Oil analysis mainly gives information about fluid properties, contamination and wear debris. Due to excessive usage of gearbox, gear and bearing start to wear out and wear particles will be mixed with the lubricating oil. Based on the result of oil analysis, health of a machine component can be assessed and action can be taken to correct the root cause or to mitigate the developing failure.

(e) Acoustic emission (AE)

AE monitoring is one of the important condition monitoring techniques for the crack detection and failure detection in rotating machineries. During engine operation, due to the rapid release of energy from the gearbox material surface or from the localized sources in a gear tooth material, a transient elastic wave is created. This wave is acquired by the device called AE sensor. Tooth breakage, impact of the bearing faults at the housing, crack formation and propagation, plastic deformation in the shear zone, are the major sources of AE in gearbox. By using this AE technique, the condition of the gearbox (wear, tooth breakage/chipping) and/or engine conditions can be easily analyzed.

(f) Vibration monitoring

Vibration analysis is widely used in the large industries to monitor the machines and their components. Vibration occurs due to the interaction between the worn tooth surface and the mating surface of gear tooth during operation. Variation in applied torque and crankshaft rotation could also be the reason for vibration. Vibration characteristics such as frequency and amplitude will be varied as the gear tooth wear or bearing fault occurs. Many failure modes of the gearbox in IC engine can be revealed in the vibration signals. The vibration signal can be easily measured by using accelerometer. In CM techniques, more than 70 % of monitoring is based on vibration signals. The literature on gearbox fault diagnosis using vibration signals will be explained in section 2.4.

In indirect measurement, signal processing involves analyzing collected signals in order to extract, display, analyze, interpret, transform the information contained in the signals to another type of signal that may be useful. The signal is then examined further using artificial intelligence and/or machine learning techniques in order to build a decision-making system (Kumar and Hirani 2021; Li and Chen 2013; Sharma et al. 2017). The details of signal processing techniques, machine learning techniques and deep learning approaches are discussed in chapter 3.

This thesis makes an attempt to explain gearbox fault diagnosis using vibration signals through basic signal processing techniques, machine learning techniques and deep learning techniques. The next part will briefly describe the gearbox of an IC engine and the various gearbox conditions included in the current study.

1.5 GEARBOX FAULT CONDITIONS

The most widely studied IC engine gearbox faults are gear tooth wear, breakage (fracture), pitting on gear, crack in the gear tooth, bearing defects at races and ball.

1.5.1 Gear tooth defect

GB consists of a different number of gears in primary and secondary shaft along with bearings at the end for supporting and to carry the loads at various capacities. GB faults such as gear tooth defect, pitting, bearing defect, etc., can lead to increased level of noise and vibration which causes severe damage to the IC engine components and also distresses the smooth running of the GB. Figure 1.2, shows the gear tooth failure modes, as depicted by (Amarnath and Praveen Krishna 2014).

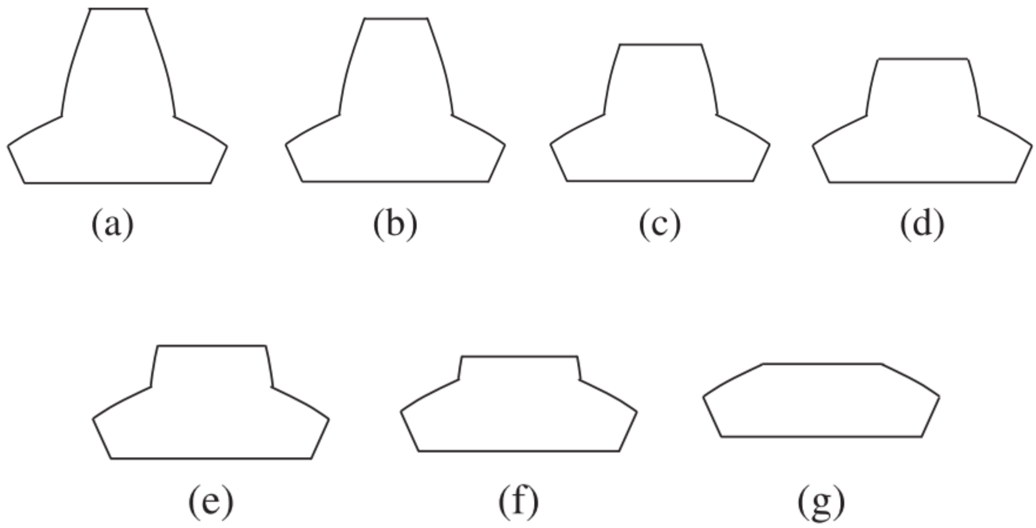


Figure 1.2 Gear tooth with (a) healthy and (b)-(g) tooth removal at progressive rate (Amarnath and Praveen Krishna 2014)

They considered healthy gear and gear with six stages of depth wise tooth removal i.e., 0%, 10%, 20%, 40%, 60%, 80% and 100% tooth removal conditions across the tooth width. Gear tooth wear are generally accepted as the normal tooth failure modes, because the other failure modes can be avoided by selecting the proper operating parameters. Also, many researchers worked on fault diagnosis of gearbox. Peng et al. (2016) conducted fault diagnosis of drivetrain gearbox using fusion of vibration and current signals. Barbieri et al. (2019) carried out analysis of automotive gearbox faults using vibration signal. Inturi et al. (2021) performed wind turbine gearbox fault diagnosis through adaptive condition monitoring system.

1.5.2 Bearing defects

In automobile engines, ball bearing is one of the major rotating machine components and plays an important role in engines. Bearing failure occurs due to improper design, contamination, corrosion, poor fitting, distorted components, misalignment, fatigue, inadequate internal clearance and low lubrication during assembling in the working unit. It is highly necessary to detect early failure in the ball bearing to avoid a catastrophic failure of an engine during operation. the most commonly used conditions for diagnosis of ball bearing are (i) inner race defect, (ii) outer race defect, (iii) rolling element or ball fault. Figure 1.3, shows the bearing failure modes, as depicted by (Ding et al. 2020).

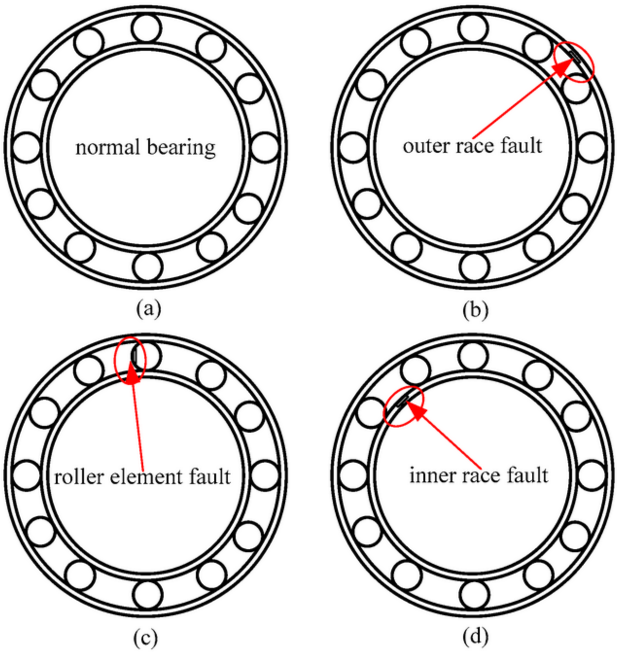


Figure 1.3 Bearing conditions (a) Normal/healthy, (b) Outer race fault, (c) roller element fault, (d) inner race fault (Ding et al. 2020)

Ball bearings are extensively used in rotating machines like IC engines, wind mills, turbines, generators, centrifugal pumps, etc. Bearing plays a major role in automobile engine gearbox. The components which frequently fail in ball bearing are inner race, outer race and rolling ball. In IC engines, early fault detection of ball bearing is highly necessary to avoid catastrophic failure of engine during running conditions. Various monitoring techniques are used to detect the fault in the ball bearing and new techniques are being developed in every year.

1.6 CONDITION MONITORING USING VIBRATION ANALYSIS

The fault diagnosis procedure is important in condition-based maintenance which comprises of two steps: data collection and interpretation. Continuous or periodic recording of data can be used to diagnose the issue by processing, analyzing and then interpreting the data. Monitoring the amount and rate of change of measured or computed variables indicates the conditions of defective gearbox. Vibration monitoring, acoustic emission detection, sound detection, lubricating oil analysis, wear debris analysis and infrared thermography are only a few of fault diagnosis techniques presently used in the industry. Each method has distinct benefits and may be used for a variety of industrial applications. Among these, vibration-based monitoring is often used as an efficient method for identifying gearbox defects (Praveenkumar et al. 2018).

Vibration generated from the gearbox contains vital information of the state of gearbox and it can be used to identify developing problems. Regular vibration monitoring can help to detect deterioration or defective conditions. Based on literature review, almost 70% of real time applications of gearbox condition monitoring system are based on vibration signal driven systems. Condition monitoring of gearbox systems can be classified as

- Monitoring based on signal processing techniques
- Monitoring based on machine learning techniques
- Monitoring based on deep learning techniques

1.6.1 Fault detection using signal processing techniques

In IC engine, vibration of the engine gearbox is based on the operating speed and applied load. The applied load varies due to gearbox condition (healthy/faulty) and correspondingly the vibration pattern will alter. These variations in the acquired signal can be analyzed in such a way that the rate at which the change in dynamic force per unit time is measured and the characteristics of vibrations are derived from the vibration patterns obtained. Each component in the system has its own frequency which can be determined from its dimensions, rotating speed etc. The condition of those components can be analyzed through signal processing techniques such as time-domain, spectrum, cepstrum, wavelet analysis etc. A brief introduction about the traditional signal processing techniques are as follows.

1.6.1.1 Time-domain analysis

The time-series plot is expressed in terms of amplitude and phase information of the acquired signal. In the present study, the acquired signals such as vibration signals will be analyzed through time series plots in order to identify the condition of the gearbox conditions.

1.6.1.2 Spectrum analysis

Spectral analysis or Fourier transform is a most widely used technique in vibration signal analysis. It converts given signal from time domain to frequency domain by integrating the given function over the entire time period. By using the characteristic frequency of components, faulty conditions can be identified. This type of vibration analysis is called as frequency domain or spectral analysis which relates frequency to its components and is widely used as basic approach. In IC engine, frequency components such as crank shaft rotational frequency (CRF), gear mesh frequency (GMF) are considered as key terms in spectrum of acquired signal to recognize the gearbox condition. The detailed analysis of spectra in terms of CRF and GMF using vibration signals will be discussed in Chapter 4.

1.6.1.3 Cepstrum analysis

The Cepsrtum analysis is another kind of signal processing method. The cepstrum was originally referred as the power spectrum of the logarithmic power spectrum. The cepstrum plots provide the information about the condition of the gearbox by investigating the quefrency component in the acquired signal. The detailed study of vibration signals of the gearbox conditions is explained in Chapter 4.

However, in IC engine, the generated signal from the gearbox may be non-stationary and non-linear in nature. These conventional methods such as time and frequency domain techniques are not suitable to analyze the non-stationary signals. This leads to the next level of vibration analysis techniques which are highly machine specific such as wavelet transform methods.

1.6.1.4 Wavelet analysis

Conventional data processing is computed in time or frequency domain. Wavelet processing method combines both time and frequency information. Wavelet analysis provides the ‘time-frequency’ information in a single plot. The continuous wavelet transform method is one type of wavelet analysis and it is used to investigate the gearbox condition in the present study.

1.6.2 Fault diagnosis based on machine learning techniques

Machine learning is a technique which is used to train the model with the help of training dataset. Based on the information available in the training data, it creates some threshold values for classification. Then the trained model analyses and classifies the testing dataset using these threshold values. In machine learning technique, the monitoring task is performed by classifying the given data. The data is investigated in several consecutive steps. These steps are feature extraction, feature selection and feature classification respectively. Figure 1.4 illustrates the steps involved in machine learning technique.

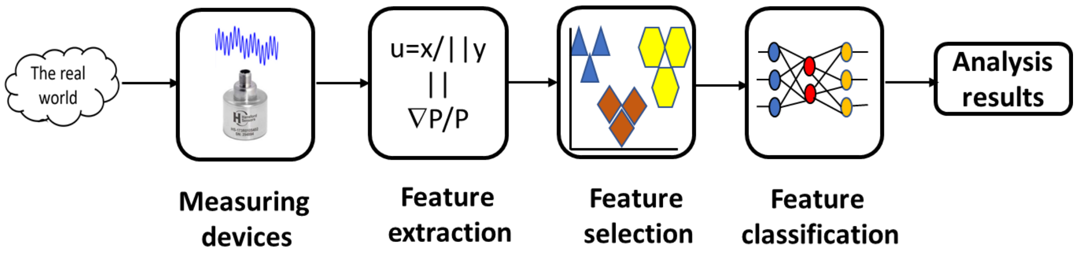


Figure 1.4 Machine learning steps

Machine learning methods address most of the problems and are proved to be a stronger method. Researchers have reported the capability of many machine learning techniques to perform fault diagnosis. Feature extraction and feature classification are the most important phases in machine learning techniques. The following subsections will give a brief introduction about feature extraction, feature selection and feature classification phases of machine learning approach.

1.6.2.1 Feature extraction

After acquiring the signals from the system, extracting the information from the acquired data and reducing the dimension of them, each data will be transformed into a reduced representation called feature vector. This transformation process is called feature extraction. Many features such as, statistical features, empirical mode decomposition (EMD) features, histogram features, etc. can be seen in the area of fault diagnosis and condition monitoring. In the present study, for feature extraction, methods such as statistical, discrete wavelet transform (DWT) and EMD techniques are applied to vibration signals. A detailed study of extracting the above-mentioned features will be discussed in the Chapter 5. After feature extraction, the salient features is selected using feature selection method. A brief note on feature selection phase is explained in the forthcoming section.

1.6.2.2 Feature selection

In the second step, the redundant features will be omitted from the feature vector. Before classifying the conditions of the gearbox, feature selection method is applied to select the salient features. The decision tree, principal component analysis, etc. are the dimensionality reduction methods in fault diagnosis. The decision tree technique is used as a feature selection method in the present study, because the decision tree (J48 algorithm) is the best method for feature selection in the area of condition monitoring (Elangovan et al. 2010). The following section reports a brief explanation on the process of feature classification.

1.6.2.3 Feature classification

Classification methods categorize feature vectors into the determined groups and completes the monitoring process. Artificial intelligence methods are often applied in the classification step and make the monitoring algorithm intelligent (Sadat and Rooteh 2013). The classification of the gearbox conditions is carried out based on selected features using artificial intelligent techniques such as support vector machine (SVM), random forest algorithm and K star algorithm as classifiers in the present research work.

Very few researchers have reported the analysis of vibration signals for fault diagnosis of the IC engine gearbox using machine learning techniques. Hence, a detailed study is required in this field. In the past decade, advanced signal processing methods have played a vital role in the area of fault diagnosis and condition monitoring. Also, in machine learning approach, the combination of an artificial intelligent technique and the feature extraction method has provided good results in some applications. However, that combination cannot ensure the same results to all other applications. Thus, there is a need for identifying the best feature-classifier combination using vibration signals in fault diagnosis of the IC engine gearbox. Machine learning based automated fault diagnosis of the gearbox of an IC engine is very essential for automotive, aerospace and industrial applications etc. Hence, in the current research work, the focus is more on these techniques to monitor the health of the gearbox.

The knowledge base of different domains and applications can be quite different and often requires extensive specialized expertise within each field, making it difficult to perform appropriate feature extraction, or maintain a good level of transferability of machine learning models trained in one domain to be generalized or transferred to other contexts or settings. Recently, deep learning techniques are being used in the field of condition monitoring or fault diagnosis. Traditional machine learning performs better with a smaller number of classification problems. However, it has some limitations such as (i) manual feature extraction, (ii) requires expertise in the signal processing, (iii) difficult to implement in real time.

1.6.3 Fault diagnosis based on deep learning techniques

Traditional feature learning includes constructing features from the input signal, searching for relevant and important features using optimum or heuristic methods, selecting relevant and important features using filter or wrapper methods and feeding the selected features into a classification algorithm. The advantage of deep learning (DL) based feature learning is that it eliminates the need of manual feature extraction and selection process. This occurs automatically within the DL framework.

DL is a subset of machine learning that achieves great power and flexibility by learning to represent the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts and more abstract representations computed from less abstract ones. The trend of transitioning from classical machine learning algorithms to deep learning can be attributed to the following reasons (Zhang et al. 2020).

- data explosion
- algorithm evolution
- hardware evolution

All of the above factors contribute to the new era of applying DL algorithms to a variety of data-related applications. Specifically, advantages of applying DL algorithms compared to classical ML algorithms include:

- Best in class performance
- Automatic feature extraction
- Transferability

Therefore, it is considered important to investigate the nature of the signals and their dependency on gearbox conditions, specifically for a gear and bearing conditions. This study deals with the fault diagnosis of the gearbox using signal processing techniques, machine learning techniques and deep learning techniques using vibration signals.

1.7 OUTLINE OF THE THESIS

Present thesis has been divided into 7 chapters following each paragraph will give a brief note on each chapter.

Chapter 1 introduces the condition monitoring of the gearbox and IC engine, importance of the IC engine monitoring, gearbox monitoring techniques, signals used for gearbox monitoring, methods of condition monitoring techniques, different faults of bearing and gear, machine learning and deep learning techniques. This chapter also brings out the brief introduction about monitoring methods used for vibration signals of gearbox of an engine and the outline of the thesis can also be seen.

Chapter 2 presents a detailed literature review on condition monitoring techniques, specifically, signal processing techniques and machine learning techniques in different fields of applications. The usage of deep learning techniques in fault diagnosis of mechanical elements are explained. Literature on fault diagnosis of IC engine, gear, bearing and other rotating elements is presented. The motivation for the present study, objective and scope of the research work is defined in this chapter.

Chapter 3 describes the methodology involved in fault detection and classification of the IC engine gearbox health conditions. The detailed explanation about signal processing techniques is discussed. Machine learning steps such as feature extraction, feature selection and classification methods are explained. Also, deep learning methods can be seen in this chapter. The details of experimental setup of two stroke and four stroke engine gearbox, experimental procedure, description of measuring instrument, conditions of gear and ball bearing used in the test can be seen.

Chapter 4 gives the results and discussion of two stroke engine gearbox fault detection and four stroke engine gear tooth defect conditions using vibration analysis. In this study, time domain analysis, spectrum analysis, cepstrum analysis and continuous wavelet transform method are used for analyzing the vibration signals.

Chapter 5 is dedicated for investigation of vibration signals through machine learning techniques i.e. (i) feature extraction methods such as statistical features, EMD features and DWT features, (ii) feature selection using decision tree technique and (iii) feature classification using classifiers such as Support vector machine, K-star algorithm and random forest algorithm.

Chapter 6 explains the application of deep learning techniques in diagnosing the gearbox fault conditions. Also, two different model were implemented and discussed for classifying the gearbox conditions. Results obtained from the deep learning model are discussed.

Chapter 7 concludes the findings of the research work, presents the future scope of this study and provides the key contributions from the study. This section is followed by the references and the list of publications.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Recent and major contributions to the state of the art in the diverse and complex areas of gearbox in IC engines are discussed in this chapter, with an emphasis on fault detection and diagnosis of the system. The following is a summary of the literature reviewed.

Condition monitoring (CM) of rotating machines is picking up significance in the industry as a result of the need to build unwavering quality and to reduce conceivable loss because of machine breakdown (Chen et al. 2021; Dellomo 1999; Elforjani et al. 2012; Jing et al. 2019; Laala et al. 2020; Samanta 2004; Sharma and Sukhjeet 2018). There are two important monitoring approaches used in condition monitoring: offline monitoring and online monitoring. Offline monitoring is related to a variety of signal processing techniques for the analysis of rotating or reciprocating machine vibration data. This approach collects data using vibration measuring sensor such as an accelerometer. After data collection, it may be analyzed using a different signal processing techniques, including time domain, frequency domain, cepstrum analysis and wavelet transform techniques. Then, based on the interpretation of the data, the machine health condition can be determined. In the case of online monitoring approach, real-time condition monitoring of a machine is possible since data from machine is continuously provided into various machine learning algorithms via a vibration measuring sensors. Data can be analyzed by identifying signal characteristics such as statistical features, histogram features and empirical mode decomposition features. The decision tree algorithm is used for selecting significant features and selected features are used as input for classification purposes. Different classifiers have been developed for different applications and one must determine the most appropriate classifier by comparing it to other classifiers. On the basis of classification accuracy, one can easily differentiate the classes of various machine faults.

Many researchers have worked in the field of rotating machine condition monitoring, considering a number of factors and developed a various fault diagnosis technique. In the following section review of the literature is discussed.

2.2 FAULT DIAGNOSIS OF IC ENGINE

Machine fault can be identified using several approaches such as vibration analysis (Joshuva and Sugumaran 2017), sound analysis (Amarnath et al. 2013; Madhusudana et al. 2017), oil analysis (Li and Liang 2011), temperature (Younus and Yang 2012), acoustic emission (Toutountzakis et al. 2005) etc. In the above methods, a vibration-based investigation is the most extensively used method for identifying the health status of rotating components (Al-Badour et al. 2011; Betta et al. 2002; Sakthivel et al. 2014; Wang and Hu 2006). The vibration signals are analyzed by signal processing methods such as time domain, spectrum analysis, statistical approaches etc. The results obtained from the spectrum analysis gives the information of frequency with amplitude variation for different conditions. However, in complex machinery, it is challenging task to identify defects through the above methods and it takes more time for analyzing individual frequency components. To avoid unnecessary failures and machine downtime, one has to adopt condition-based monitoring which provides information regularly and based on the results obtained, scheduled maintenance can be planned. To understand the cause for the fault, continuous monitoring needs to be done using machine learning (ML) approach. The fault diagnosis of spark ignition (SI) IC engine has become one of the dominant areas of research over the decade. Most of the researchers used a combustion parameter for analyzing the defects in engine components.

Currently, with the higher engine speed, power and performance, there is tremendous scope in developing online condition monitoring of the automobiles and other rotating equipment (Moosavian et al. 2017). Following literature addresses condition-based monitoring employed on IC engine/rotating machineries.

Lee et al. (1998) analyzed the vibration signals and impulsive sound to detect the fault in rotating machinery parts. These impulsive sound signals were characterized by using adaptive line enhancer (ALE) in two stages. This algorithm was applied to diagnose the IC engine faults and industrial gearbox fault. Samimy and Rizzoni (1994) carried out experiments on improving knock detection with the application of joint time-frequency analysis. In this analysis, engine block vibration and pressure signals were used for knock detection. Time-varying filters were used to reduce noise in the vibration signals. Results showed that the proposed method was provided good accuracy in detecting engine knock. In the conventional method of condition monitoring, Fast Fourier transform (FFT) technique was used to identify the defective components based on characteristic frequency (CF) of acquired signals (Rai and Mohanty 2007). However, in a complex system like an IC engine GB, it is very difficult to identify the CF of each component. Even if CF is determined, the signals obtained from the GB are highly non-stationary and FFT alone may not be suitable for identifying the conditions of the GB (Muralidharan et al. 2014b). Moreover, the conventional method of fault diagnosis cannot handle a large amount of data efficiently. A significant development of the internet era is the attention given to the data-driven approach for fault diagnosis which has better accuracy compared to physics-based models (Wang et al. 2019). Some of the literature focused on fault diagnosis of IC engine by various acquisition system and diagnosis method are discussed here.

Ettefagh et al. (2008) found knock detection in SI engine using vibration signals. They proposed a method for modelling cylinder block by autoregressive moving average (ARMA) parametric model. Wu and Liu (2009) developed an expert system for diagnosing faults in the IC engine using sound emission signals. They adopted wavelet packet and artificial neural network (ANN) for classification of engine faults. Klinchaeam and Nivesrangsan (2010) investigated valve clearance fault in the petrol engine. Experiments were conducted with intake/exhaust valve fault conditions. Vibration signals were acquired for both cases and they used the energy analysis technique to identify the faults. Moosavian et al. (2013) made an attempt for diagnosing faults in the main journal bearing of an IC engine based on power spectral density techniques using two classifiers such as ANN and k-Nearest Neighbour (kNN). The results showed that the proposed method can be effectively used for bearing fault diagnosis. Sharma et al. (2014) inspected misfire in IC engine by exploiting vibration signals and a J48-decision tree. They extracted statistical features from the signals and comparative study of tree-based classifiers was made.

In recent years, vibration-based fault diagnosis techniques attracted many researchers to diagnose the engine components viz cylinder liner, piston scuffing and piston scratching (Jiang et al. 2017; Moosavian et al. 2016, 2017; Ramteke et al. 2020). Moosavian et al. (2016) investigated piston scuffing fault and its effect on engine performance. Vibration signals were acquired for diagnosing the piston defects and results showed that vibration analysis was efficient in identifying the scuffing faults. Jiang et al. (2017) studied fault detection of valve clearance in IC engine using cylinder head vibration signals. Experimental results illustrated that the proposed technique was capable of diagnosing valve clearance. Ramteke et al. (2020) attempted to detect cylinder liner fault using vibration and acoustic signals in a diesel engine. Figure 2.1 illustrates the vibration and sound signal-based cylinder liner fault diagnosis of the diesel engine test setup (Ramteke et al. 2020). They obtained a higher amplitude of vibration and acoustic signals with liner defect in the cylinder. Also, they extracted a few statistical features for classifying the liner fault.

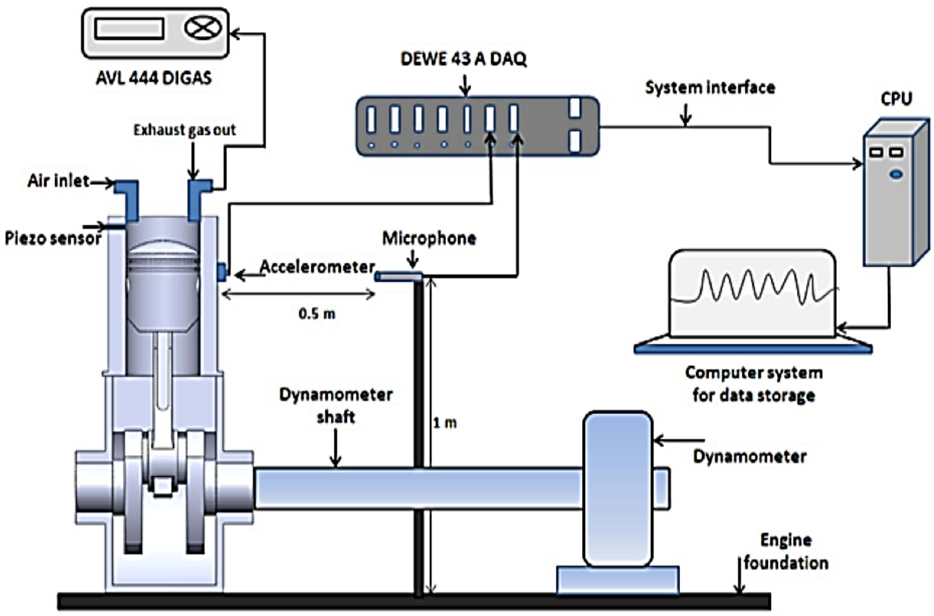


Figure 2.1 Cylinder liner fault diagnosis test setup of diesel engine (Ramteke et al. 2020)

Moosavian et al. (2016) studied IC engine piston scuffing and its identification using vibration signals. Three-body wear mechanisms method was adopted to induce defects in the piston. Signals of the engine were analyzed using continuous wavelet transform for finding piston defect. Haneef et al. (2017) used numerical method for investigating bearing defect using vibration signal in IC engine. Jafarian et al. (2018) carried out identification of misfire and valve clearance in the combustion chamber of the engine using multiple sensor vibration signal analysis. They considered FFT technique for feature extraction from vibration signals. Engine malfunction was classified using different classifiers such as ANN, support vector machine (SVM) and KNN.

2.3 FAULT DIAGNOSIS OF BALL/ROLLER BEARING

Ball bearings are extensively used in rotating machines like IC engines, wind mills, turbines, generators, centrifugal pumps, etc. Bearing plays a major role in automobile engine gearbox. The components which frequently fail in ball bearing are inner race, outer race and rolling ball. In IC engines, early fault detection of ball bearing is highly necessary to avoid catastrophic failure of engine during running conditions. Various monitoring techniques are used to detect the fault in the ball bearing and new methods are being developed in recent years. Vibration based techniques are most generally used for fault diagnosis of bearing since local defects in the bearing produced successive impulses on contact surface of the bearing and hence housing structure is forced to vibrate at different level.

The utilization of vibration and acoustic emission signal is very common in the field of CM of rotating machines. By comparing the signals of a machine operating in healthy and defective conditions, recognition of flaws like rotor rub, mass unbalance, misalignment in shafts, bearing defects and gear defect is possible. These signals can be used to distinguish the beginning of faults developed in the machine elements. With the use of online monitoring system, catastrophic failures and machine downtime can be reduced (Madhavan et al. (2014); Vernekar et al. (2014)). There are two steps involved in the fault diagnosis of ball bearing, first one is to extract feature from the acquired vibration signals and next one is to analyze/classify different conditions of the ball bearing using these extracted features.

Rolling element bearings are critical machine component in all rotating machines and monitoring of such member is very important to avoid failure (Tandon et al. 2007). Roller bearing is used in most of the rotating machines and fault prone due to fatigue and severe working conditions such as lacking in lubrication, heavy and impact loading. In most of machine failure cases faulty bearing is considered as the foremost cause of failure (Lou and Loparo 2004). Tandon and Choudhury (2000) studied the vibration and acoustic measurement method for finding the defects in rolling element bearings. Authors gave a detailed discussion about the various techniques used for detecting the localized defects, distributed defects and the frequencies of the defective rolling bearing elements. Vibration measurement in both time and frequency domains along with signal processing techniques such as the high-frequency resonance technique were discussed. McInerny and Dai (2003) have presented a paper on basic vibration signal processing for bearing fault detection in which characteristic fault frequencies of ball bearings were explained and one of the bearing fault detection techniques, traditional spectral analysis has been dealt. Tandon et al. (2007) used acoustic emission and shock pulse method (SPM) for measurement of fault detection in bearing, on comparing the results of healthy and faulty conditions of bearing AE gave more information about the peak amplitude and SPM gave a normalized value level that is much higher compare to all other methods.

Amarnath et al. (2013) reported the study of fault diagnosis of ball bearing using sound signals. These acquired signals with healthy and different faulty conditions of bearing were analyzed using machine learning approach. From the sound signal, the descriptive statistical features were extracted and important features were selected from the decision tree. Classification of selected features was done by using C4.5 decision tree algorithm. Figure 2.2 illustrates the sound signal-based condition monitoring of the bearing test setup (Amarnath et al. 2013). Kiral and Karagülle (2006) found a method based on finite element vibration analysis for fault identification in roller bearing with single or multiple faults on various components of the bearing structure using time and frequency domain parameters.

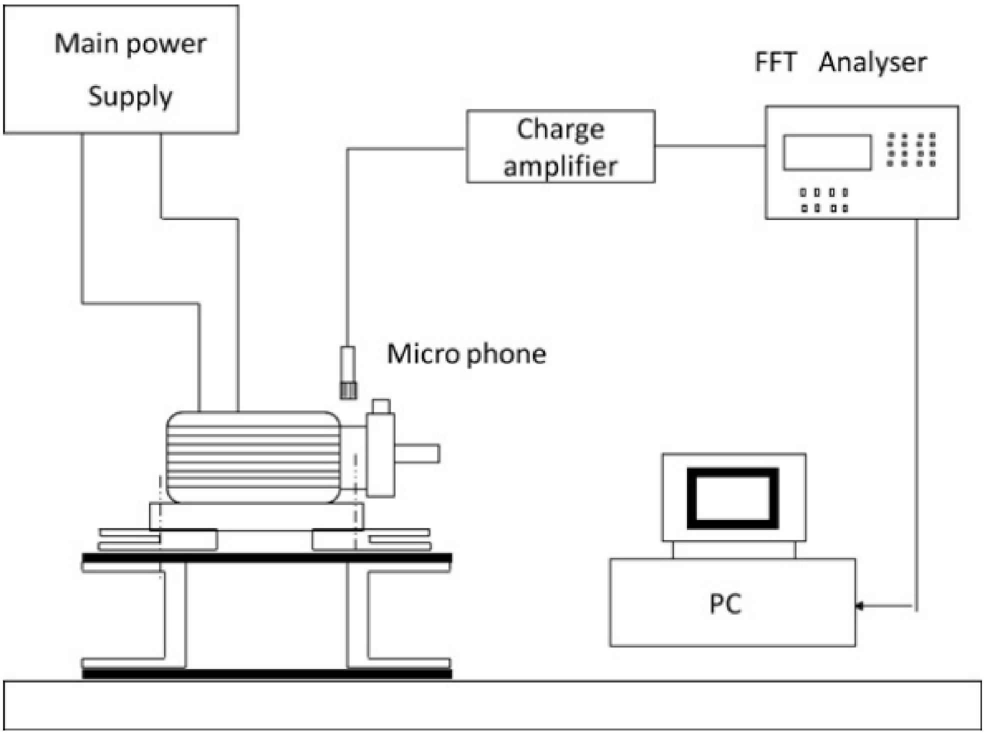


Figure 2.2 Sound based experimental setup for fault diagnosis of bearing (Amarnath et al. 2013)

Liu et al. (2013) worked and presented a paper on multi fault classification model based on the kernel method of SVM and wavelet frame, wavelet basis was presented to develop the kernel function of SVM and wavelet support vector machine (WSVM). Wang et al. (2014) presented a paper on a new method to identify compound faults from measured, mixed signals of roller bearing which is based on two methods, ensemble empirical mode decomposition (EEMD) and independent component analysis (ICA) technique. Comparing with conventional methods like FFT based Hilbert transform (HT), wavelet analysis and EEMD method the results are classified more effectively in proposed method. Zhu et al. (2014) proposed a novel measurement method based on the null space pursuit and S-transforms for fault detection in bearing vibration signal. Experimental results are indicated the identification of the fault frequency of the bearing signal. From the literature, one can notice that vibration analysis can be used for rotating machinery fault diagnosis. However, literatures were limited in the field of condition monitoring of IC engine ball bearing. Hence, there is need for studying vibration signals of IC engine to identify defects in the ball bearing.

2.4 FAULT DIAGNOSIS OF GEARS

Chen et al. (2013) proposed a novel intelligence diagnosis model based on wavelet SVM and the immune genetic algorithm. The features selected from the vibration signal are preprocessed by EMD. The results of experiment indicating that the proposed method was more effective in fault diagnosis of bearing. Antoniadou et al. (2015) investigated gear fault under various conditions by using EMD to decompose the vibration signals into sensitive signal components associated with definite frequency bands of the signal. Figure 2.3 illustrates the vibration-based back-to-back gearbox fault diagnosis test setup (Hong and Dhupia 2014).

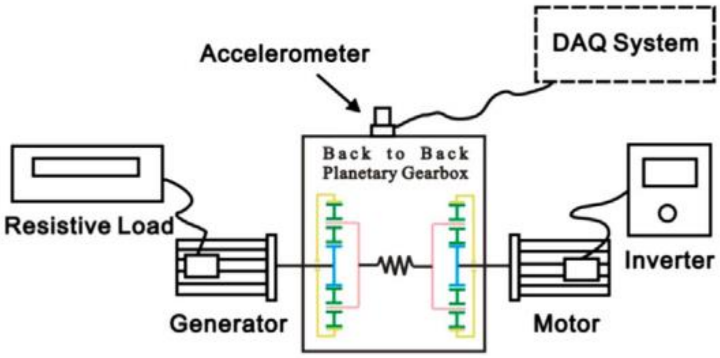


Figure 2.3 Vibration based fault detection of gearbox test rig (Hong and Dhupia 2014)

Hong et al. (2014) studied and formulated the fault detection of planetary gear box based on feature extraction algorithms. Fourier series analysis was used to explain distinct sidebands which contain important information of diagnostics. Li et al. (2009) investigated the gear fault detection using newly developed order cepstrum and radial basis function (RBF) and ANN during machine speed up process. In this method, non-stationary signals are converted it into stationary signals using computer order tracking technique. Jena et al. (2013) carried out an experiment for gear fault detection using analytical wavelet transform.

Amarnath and Praveen (2014) carried out fault identification in helical gears, based on vibration and acoustic signals using EMD with statistical analysis. Yu et al. (2016) proposed a new method for compound fault diagnosis of gearbox using morphological component analysis. This method could identify fault in the gearbox corresponding to bearing defect and gear defect. Sawalhi and Randall (2014) identified different gear parameters of a wind turbine based on vibration signals. The gearbox with one planetary gear and two helical gears in parallel stages individually were studied. Muralidharan et al. (2015) presented the fault diagnosis of helical gearbox using vibration signals. Variational mode decomposition (VMD) method was used for analyzing signals and statistical features extracted from the VMD. These features were used for classification of fault conditions using different decision tree algorithm and results provided satisfactory efficiency in classifying fault condition of gear.

Heidari and Ohadi (2014) studied gearbox fault identification based on vibration signals under varying speed conditions using the wavelet transform and Shannon entropy for feature extraction. Elasha et al. (2015) investigated pitting detection in worm gearbox based on vibration analysis. Three different worm gearboxes were studied using vibration analysis involving three different techniques, namely, statistical analysis, spectral kurtosis and enveloping. Konar and Chattopadhyay (2015) used wavelet and Hilbert transform for detecting multi-class fault diagnosis in the induction motor using vibration signals in the radial direction.

2.5 FAULT DIAGNOSIS OF OTHER MACHINE ELEMENTS

Madhusudana et al. (2016b) identified milling tool conditions using vibration analysis through signal processing techniques like spectrum, cepstrum and wavelet transform analysis. Figure 2.4 shows the test setup used for milling tool monitoring using vibration analysis. Muralidharan et al. (2014a) identified different faults in the belt conveyor carrying system using statistical feature and decision tree algorithm. Joshuva and Sugumaran (2017) carried out a comparative study of best first tree and functional tree algorithm for analyzing vibration signals of wind turbine under various conditions of blade. Bordoloi and Tiwari (2014a) performed multi fault class identification of gears using SVM with the frequency domain data. In this study, main focus was on optimizing multi class ability of SVM technique with the help of genetic algorithm, artificial bee colony algorithm and grid search method.

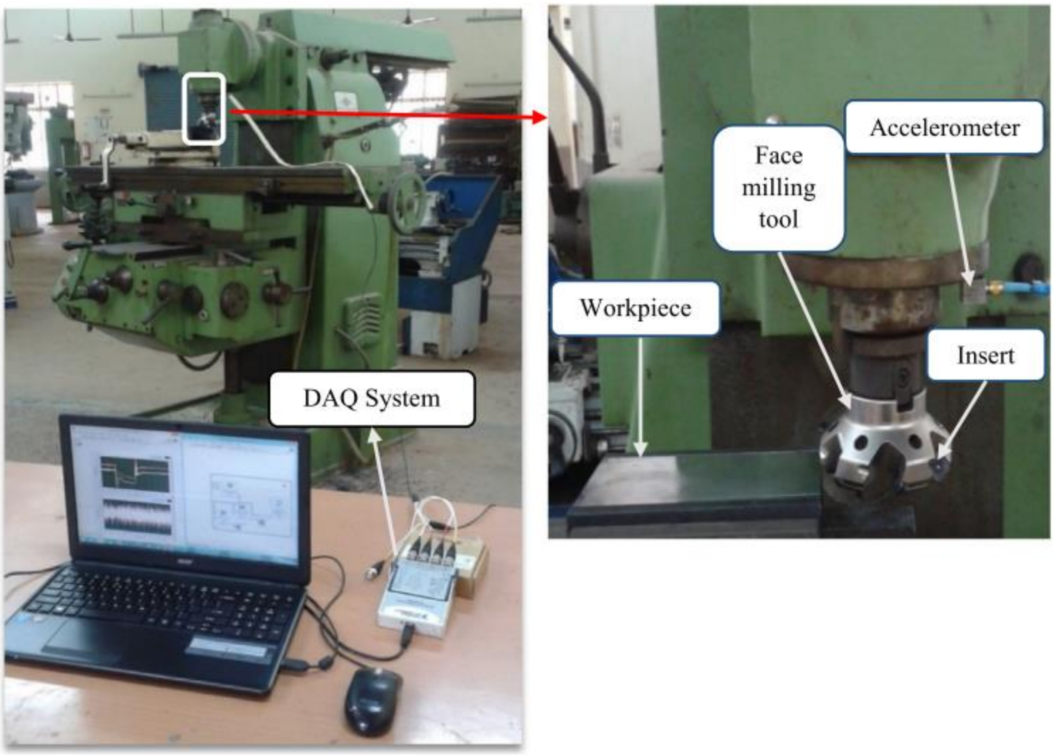


Figure 2.4 Fault diagnosis of face milling tool test setup (Madhusudana et al. 2016b)

Gangadhar et al. (2014) carried out fault diagnosis of single point cutting tool of lathe machine using vibration signals through decision tree algorithm for selection and classification of features. This algorithm gave about 89% classification accuracy in identifying tool wear condition.

2.6 SIGNAL PROCESSING TECHNIQUES

There are many numbers of different signal processing technique which are used for extracting information from signals acquired from the mechanical elements. Frequency domain analysis, cepstrum analysis and wavelet analysis belong to the signal processing techniques. A significant number of research works using these techniques have been carried out, some of them are discussed in the following sections.

2.6.1 Time domain analysis

Time domain analysis uses the time history of the signal and uses to record what happens to a parameter of the system versus time. Transducers are available to record the time domain signals of the system which in the form of displacement, velocity, acceleration etc. Accelerometer, load cells, microphone, pressure sensor are some of the commonly used transducers for measuring time domain signals.

2.6.2 Frequency domain analysis

Fourier showed that any waveform that exists in real world can be generated by adding up sine waves. In time domain signals, it is very difficult to understand the amplitude variation and frequency information is also not available in the time domain plots. The frequency domain signal or frequency spectrum is a plot of amplitude of vibration response versus the frequency and can be derived by using the Fourier Transform of the time domain signals. Fourier transforms includes some advanced techniques such as Fast Fourier transform (FFT), short time Fourier transform (STFT) and discrete Fourier transform (DFT). These are used to determine the frequency component in the acquired vibration signals.

Kar and Mohanty (2008) carried out experiments to investigate a fault in the multistage gear box under transient load. For the experiment, they considered three defective conditions and three transient loading conditions. Signals of gear box were processed using advanced techniques such as DWT and multi resolution Fourier transform (MFT). Yang et al. (2009) investigated bearing fault using vibration and current signals. FFT is used for conversion of time domain signals to frequency domain signals. Luo et al. (2012) proposed some new techniques for fault detection in gear based on multi scale chirplet path pursuit (MSCPP) and fractional Fourier transform (FRFT). Ocak and Loparo (2004) investigated bearing defect of induction motor at running speed using vibration signals from the motor. Lokesha et al. (2011) presented various signal processing methods for diagnosis of faults in a single stage gear box. They considered FFT, Morlet wavelet and Laplace wavelet for processing acquired signals under different gearbox conditions.

Ji et al. (2018) carried out experiments on a single and twelve-cylinder engine for estimating combustion parameters like peak pressure rise rate and peak combustion pressure. Surface vibration signals were considered for the analysis using frequency spectrum method. Hong and Dhupia (2014) studied and formulated the fault detection of planetary gear box based on feature extraction algorithms. Spectrum analysis method was utilized to explore distinct sidebands which contain significant evidence of diagnostics. Vashisht and Peng (2018) applied switching control and STFT for detection of crack in the ball bearing.

2.6.3 Cepstrum analysis

Cepstrum analysis is one of the signal processing techniques which clusters different frequencies corresponding to components that exists in the rotating machine/system. The cepstrum plots are used to identify the conditions of the system/cutting tool with the help of quefrency information in the acquired signals Borghesani et al. (2013) carried out experiments for fault diagnosis of rolling element ball bearing under various speed condition using cepstrum analysis. For experimental study, various faulty conditions were used and analyses were done. Liang et al. (2013) used different techniques for fault diagnosis of induction motor, namely power spectrum, cepstrum, higher order spectrum and neural network analysis. They also suggested that cepstrum analysis is very suitable for detection of harmonic family with uniform spacing or family of sidebands usually found in the gearbox, bearing and engine vibration fault spectrum. Park et al. (2013) considered a new method for early fault detection of ball bearing using the minimum variance cepstrum (MVC), experimental results are showing that MVC can be used as analysis tool for fault detection of periodic fault signals. Morsy and Achtenová (2014) used cepstrum analysis for diagnosis of vehicle gearbox. Results are clearly demonstrated that for detecting faults, cepstrum analysis was better in comparison to spectrum analysis.

2.6.4 Wavelet analysis

Wavelet analysis is new development in the area of applied mathematics and signal processing technique. Wavelet is a waveform of limited duration that has an average value of zero. Since FT is suitable only for stationary signals and fixed resolution, a new wavelet design was developed using wavelet transform to overcome the drawbacks of FT.

Many wavelets have been developed, like the continuous wavelet transform (CWT), Morlet wavelet and Discrete wavelet transform (DWT). CWT technique is has the capacity to detect non-periodic, non-stationary and transient features of acquired signals. Wu and Chen (2006) used CWT technique to diagnose the faults in IC engine along with its cooling system. The results obtained from the experiments have shown a good amount of accuracy in identifying the conditions of IC engine such as engine fault diagnosis and cooling fan blade fault conditions. Zarei and Poshtan (2007) investigated current signal to recognize the bearing defect in the induction motor using Meyer wavelet in the wavelet packet structure. Kankar et al. (2011) analyzed the vibration signal using CWT technique in order to identify the roller ball bearing condition.

Chandran et al. (2012) investigated a gear fault by applying Laplace wavelet kurtosis for processing vibration signals of the gear under various condition. Rafiee et al. (2010) proposed an automatic feature extraction algorithm for fault diagnosis of gear and bearing using wavelet transform analysis. Li et al. (2013) developed a multiscale slope feature extraction method for the rotating machinery fault diagnosis using wavelet based multi resolution analysis. In their study, bearing and gear box were tested on separate test setup. Yan et al. (2014) analyzed different wavelet transforms theories for fault diagnosis of rotary machines which include CWT based fault diagnosis, DWT based fault diagnosis, WPT based fault diagnosis and second-generation wavelet transform based fault diagnosis. Al-Badour et al. (2011) studied the diagnosis of rotating machines using time frequency and wavelet analysis. For analysis of vibration signals two wavelets were selected, namely continuous wavelet and WPT. Jena et al. (2013) investigated faults in the motor vehicle piston using sound signals. They used CWT technique with complex morlet wavelet as mother wavelet for processing acquired sound signals. Madhusudana et al. (2016) performed the experiments on fault detection of milling tool by applying different signal processing techniques such as Fourier analysis, cepstrum analysis and wavelet analysis. Results showed that the time-frequency plot of vibration signal and CWT plots provided better information compared to the plots obtained by spectrum and cepstrum analyses.

In the present study, vibration signals with associated signal processing techniques were efficiently used for detecting the condition (Healthy or defective) in the ball bearing and gear.

2.7 MACHINE LEARNING TECHNIQUES

In recent times, machine learning techniques have become the primary tools for understanding machine conditions based on the features of past data. To understand the cause of the fault, continuous monitoring needs to be done using a machine learning (ML) approach. For training features, computer algorithm is built and optimized based on the past data set of the machine. Many researchers have carried out fault diagnosis of machineries by considering machine learning techniques. In machine learning, three important steps are involved namely feature extraction, feature selection and feature classification.

2.7.1 Feature extraction

The huge number of acquired digital signals from the machine or system cannot be directly used for machine learning. The required fault information is extracted from these huge data in the form of features such as statistical features, empirical mode decomposition features, wavelet features, etc. The following subsections will provide the usage of different features in condition monitoring and fault diagnosis.

2.7.1.1 Statistical features

The descriptive statistical features viz. mean, mode, skewness, maximum, minimum, standard error, range, median, sample variance, sum, standard deviation and kurtosis are estimated from the acquired signals. These twelve features are some of the statistical parameters that have been used widely for the research work in the area of condition monitoring and fault diagnosis. Jegadeeshwaran and Sugumaran (2015) investigated a fault diagnosis of automotive hydraulic brake system using statistical features of vibration signals of the system under different condition. Saimurugan et al. (2016) diagnosed on-road gearbox fault using vibration signal by inducing artificial fault on gear tooth. Authors extracted statistical features and used decision tree for feature selection and classification. Gangadhar et al. (2014b) carried out fault diagnosis of lathe machine single point cutting tool by employing statistical features of vibration signals.

2.7.1.2 Empirical mode decomposition features

EMD is method used to decompose complex signals in to finite or small number of components. These components are called as intrinsic mode functions (IMF). EMD is used to decompose raw vibration signals into IMFs that represent the oscillatory modes generated by the components of the mechanical systems.

Ghaderi and Kabiri (2017) demonstrated automobile engine fault diagnosis through sound signal by employing EMD on acquired signals. Best-first algorithm was used to ignore irrelevant features. Three classifiers were used for classification and were compared amongst for their classification accuracy. Amarnath and Praveen (2012) showed that EMD based statistical features are effective in detecting early failure in roller bearing and helical gear unlike time domain statistical features which are susceptible to noise and non-stationary characteristic of acquired acoustic signal. The approach considered only a few fault conditions and used a single (EMD) feature extractor for diagnosis. Lei et al. (2013) reviewed a fault diagnosis of machine components such as rolling bearings, gears and rotors by using EMD technique. Dybala and Zimroz (2014) carried out a rolling ball bearing diagnosis using EMD technique. Liu et al. (2015) presented bearing fault diagnosis based on least squares support vector machine (LS-SVM) and EMD. The weighted LS-SVM was used to remove the high-frequency intermittent noises, LS-SVM rolling prediction model was applied to extrapolate the signal and spine cubic interpolation is replaced by LS-SVM regression to reduce the end effects.

2.7.1.3 Discrete wavelet transforms features

DWT decomposes the signal into two frequency sub bands such as low frequency band (approximate coefficients) and high frequency band (detailed coefficients) through high pass filters and low pass filters. Subsequently, the decomposed low frequency component of the signal is again decomposed into approximate and detailed coefficients. This iteration will go on and at each step the approximate coefficient is considered as a DWT feature.

Saravanan and Ramachandran (2010) carried out fault diagnosis of gearbox using vibration signals. They extracted DWT features from the vibration signals and classification was done using ANN. Wu and Kuo (2009) presented fault diagnosis of an automotive generator using DWT features and ANN for fault classification. Saravanan and Ramachandran (2009) studied the gear fault diagnosis using DWT feature and J48 decision tree for selection and classification of features. Wu and Liu (2008) carried out fault diagnosis of IC engine using DWT and neural network. Wu et al. (2009) studied gear fault classification using vibration signals. They used DWT and adaptive neuro-fuzzy inference system (ANFIS) method for fault identification in the gear.

2.7.2 Feature selection

All extracted features from measured data are not required to extract the diagnostic information. Dimensionality reduction techniques remove the redundant information to reduce the original higher dimension for the ease of processing and computation. Recently, the use of feature reduction and feature selection for data preparation before feeding into the classifier has received considerable attention (Cao et al. 2003). In the present study decision tree was used for selecting significant features from the feature vector. It is the procedure used to select subset of 'M' features from the existing set of 'N' features (M<N). The role of the feature selection in machine learning system are as follows;

➢ It enables the machine learning algorithm to train faster

➢ It reduces the complexity of a model and makes it easier to interpret

➢ It improves the accuracy of a model if the right subset is chosen and

➢ It reduces overfitting

The details of the usage of feature selection technique are discussed in the following sections.

2.7.2.1 Decision tree technique

Decision tree technique is widely used in machine learning and classification fields. Decision tree can be used for both feature selection and classification of features. A decision tree is a tree-based knowledge representation methodology used to represent classification rules. J48 algorithm (A WEKA implementation of C4.5 algorithm) is a widely used technique to construct decision trees (Sugumaran et al. 2007). Saimurugan et al. (2011) considered decision tree for selecting important features from the vibration signals of rotating system. Jegadeeshwaran and Sugumaran (2015) presented fault diagnosis of automobile hydraulic brake system using C4.5 decision tree algorithm for feature selection and SVM algorithm for classification. Sun et al. (2007) presented a fault diagnosis of rotating machinery based on decision tree and principal component analysis (PCA) based algorithms. Krishnakumari et al. (2016) conducted fault diagnosis of spur gear using decision tree and fuzzy classifier. They extracted statistical features from the vibration signals then feature selection was performed by J48 decision tree algorithm. Vernekar et al. (2015) carried out fault diagnosis of IC engine gearbox using DWT feature. They used decision tree for selecting features and SVM was used as classifier for classification of features. Kumar et al. (2019) studied multi sensor data fusion for fault diagnosis of gearbox using DWT features. They used decision tree for selecting contributing features and ANN, SVM, PSVM as classifiers for classification.

2.7.3 Classification of features

Feature classification is the last phase of the machine learning approach. In the classification process, the classification algorithm develops a model with the help of training data and the trained model is used to classify the data belonging to various classes of faults. There are various classification techniques to classify the gearbox conditions. ANN, SVM, Naïve Bayes and K-star algorithm are used by many researchers in the fault diagnosis of rotating machineries. The following subsections provide the details about the use of classification algorithms for online IC engine gearbox monitoring.

2.7.3.1 Support vector machine (SVM)

SVM is one of the most widely used classification algorithm in machine learning applications, because of its accuracy and good generalization capabilities (Saimurugan et al. 2011). SVM is used in many fields for classifying the data such as text recognition, face detection, biomedical, satellite data etc. SVM is a relatively new computational learning method (Cortes and Vapnik 1995). SVM was originally made for classification and nonlinear regression tasks (DEÁK et al. 2014; Vora et al. 2015). SVM is based on statistical learning theory and it works on the principle of risk minimisation. Saimurugan et al. (2011) investigated multi component fault diagnosis using vibration signals of the roller bearing. They used decision tree for selection of important features and SVM as classifiers for feature classification of vibration signal for fault detection in the roller bearing. Kankar et al. (2011) carried out rolling element ball bearing fault detection using vibration signals and continuous wavelet transform signal processing technique. In their study, fault classification is done based on three machine learning techniques, i.e., SVM, ANN and Self-Organizing Maps (SOM). From the results, they found that SVM with Meyer wavelet is giving a good amount of accuracy in identifying the faults in the roller bearing element.

2.7.3.2 K star algorithm

K star algorithm is one of the instance-based classifier algorithms. This is the class of a test instance which is based on training instances identical to it, as determined by few similarity functions. It is different from other instance-based learners in the way that it utilizes an entropy-based distance function. Instance based learners classify an instance by comparing it to a data base of pre-classified examples. The essential assumption is that similar instances will have similar classification. This algorithm uses entropic measure, based upon probability of transformation of an instance into another by random selection between all possible transformations. Taking entropy as a measure for an instance distance is very much beneficial and information theory provides an advantage in measuring the distance among the instances. A uniform method of management of real valued, symbolic and missing value attributes is obtained.

Madhusudana et al. (2016a) carried out condition monitoring of face milling tool under different conditions of tool using vibration signals. They extracted histogram features from the signals and classification was done using K star algorithm. Pawar et al. (2016) considered decision tree, K star algorithm and wavelet transform for fault diagnosis of helical gear box using vibration signals. Painuli et al. (2014) studied fault diagnosis of lathe tool monitoring using vibration analysis. Statistical features extracted from the acquired signals and classification was performed using K star algorithm. Results shows that K star was able to achieve 78% classification accuracy in classifying the conditions of the tool.

2.7.3.3 Random forest algorithm

Random Forest is a type of artificial intelligence technique to identify the state of machinery component. The Random Forest algorithm was developed by Breiman (2001)and is based on building a decision tree. In the initial stage, the training set consisting of features is divided into in-bag and out-bags set. The method of bootstrapping is repeated several times on feature set to produce several in-bag and out-bag set subsets. A decision tree is modeled for each in-bag data and the out-of-bag set is used for evaluating the classification accuracy of each decision tree. The final outcomes based on algorithm are obtained from out-bag sets from the entire training dataset. Every decision tree casts a vote for one class and this vote can be used to estimate the generalization capability of the classifier. The class from the feature set is recognized by gaining maximum vote (Peng and Chiang 2011). The Random Forest error rate depends on the correlation between any two trees in forest and strength of each tree in the forest. Increasing the correlation increases the forest error rate. On the other hand, a tree with a low error rate is a strong classifier (Vakharia et al. 2017). Cerrada et al. (2016) proposed fault diagnosis of spur gear using genetic algorithm for selecting features and random forest for classification. Classification accuracy of about 97% is achieved using the random forest algorithm. Quiroz et al. (2018) used the random forest algorithm for fault identification in an induction motor. The results of the algorithm showed improved accuracy in differentiating healthy and faulty cases of the induction motor.

2.8 LIMITATIONS OF MACHINE LEARNING TECHNIQUES

The signal processing, manual feature extraction techniques and models give good diagnosis results, but some of their limitations mentioned below.

- Feature extraction techniques require expertise in the field of signal processing. Generally, researchers use statistical, HHT, WPT and EMD for feature extraction. Hence, effectiveness of the model depends upon quality of feature extracted.
- Manual feature extraction is time consuming and laborious.
- SVM, KNN, decision tree, Bayesian network and other architectures are employed on extracted feature; which are not easy to fit on complex non-linear functions. It requires large number of hidden layers that increases computational burden.
- They can extract only limited number of faults, typically 3 to 6 types. A few of the models fail as number of fault cases increase and therefore cannot be used in real time failure analysis.

Conventional approaches such as back propagation neural network (BP-NN) and SVM have limitations such as increased computing power requirement to process huge number of datasets within time. Due to the above-mentioned shortcomings of traditional machine learning algorithms, attention was focused on ANN and its variants. ANN is composed of many simple and interconnected neurons. These neurons are connected to each other by links that have associated weights. The weights between each neuron determine the significance of the input to each neuron. As it is trained, these weights are updated as the ANN learns. Many variations of the ANN exist such as Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Deep Belief Networks (DBN) Generative Adversarial Networks (GAN). Among these, CNN and LSTM are the most popular ones for diagnostics of faults in rotating machinery. CNN is mostly used in image recognition.

2.9 DEEP LEARNING TECHNIQUES

Over last decade, researchers widely used methods like SVM, ANN, decision tree, random forest, etc. These methods were commonly used with high accuracy by extracting deep features from raw vibration signals. However, automatic feature extraction methods increased the demand in case of fault diagnosis of rotating machine elements with high accuracy and less complexity. To address the short comings of machine learning methods researchers introduced stacked LSTM, an advancement of recurrent neural networks (RNNs), for bearing fault diagnosis (Yu et al. 2019). LSTM layers have capability of manual feature extraction, which solves gradient descent problem present in RNN. They used three LSTM layer for automatic feature extraction and softmax layer for classification.

Recently, deep learning techniques are used due to their effectiveness and quality of feature extraction, recognition and classification. The deep learning model comprises of multiple layers stacked with the network to extract high-level features from raw input data and provides significant results. Deep learning techniques are used in image processing, speech recognition, natural language processing and image recognition etc. Since the vibration signal of the rotating element of mechanical systems has similar dimensionality like image processing and speech recognition, deep learning architecture can be used for fault diagnosis of mechanical components based on their raw vibration data.

Tian and Liu (2019) proposed a deep convolutional neural network (DCNN) based fault detection model. DCNN extracts features automatically from sensor signal and eliminates the need of expertise in the area of signal processing or feature engineering. Now a days, there are many deep learning techniques being used for diagnosis (Ince et al. 2016). Deep learning techniques are applied to extract features from fault bearing signals (Cabrera et al. 2017). DCNN was proposed to extract features in time and frequency domain of rolling element and antibody immunity algorithm was used for bearing fault detection in real time. Fault type was identified by comparing both time and frequency domain analysis results.

It is difficult to get accurately labelled data in industries for training which requires large amount of data sets. Thus, data augmentation is used to get additional valid labelled data for training. Li et al. (2020) proposed deep learning model based on data augmentation. Two methods of augmentation method were investigated namely datasets -based method and sample -based method. The performance of proposed model was estimated with respect to data augmentation techniques. An effective fault detection of any rotating component has always been a significant issue in mechanical industries. Zhang et al. (2019) proposed a deep learning model composed of CNN block and residual learning blocks. Using residual learning, one can go much deeper with neural networks without gradient descent or gradient explosion problem. Based on the signal analysis method, intelligent fault detection techniques have been extensively used for fault detection in rolling bearing and TCM. Chen et al. (2020) proposed a CNN and stacked LSTM based deep learning model for automatic feature learning from the raw vibration sensor signals. Researchers considered two CNNs for feature extraction and two LSTM models to find out fault type based on learned features. The multi-scale CNN and LSTM model was comprised of a feature extractor and classifier, it takes raw vibration signal directly as input without any data pre-processing operation.

Lu et al. (2017) proposed a stacked denoising auto-encoder (SDA) based deep learning model for health monitoring for a signal having ambient noise and fluctuation condition of rotating machinery component. It is a robust feature representation technique. SDA based deep learning techniques are divided into three parts: (i) division of training and testing samples; (ii) establishment of hierarchy deep learning architecture; (iii) establishment of transmitting rule for model training. The presented model achieved good accuracy of classification; however, having difficulty in network training. Sun et al. (2016) proposed a deep neural network (DNN) for fault diagnosis in induction motor, adopted sparse auto-encoder (SAE), unsupervised feature learning techniques. The SAE operates on unlabelled raw vibration datasets that help in denoising coding. The learned features were given to a neural network-based classifier for finding faults in the motor. SAE improved the robustness of features leaning with noisy data. The auto-encoder extreme learning machine (ELM) based technique was used for bearing fault diagnosis and to overcome the deficiency of previous neural networks techniques; i.e., difficulty in network training and more training time (Mao et al. 2017).

In deep learning methods, CNNs and LSTM are specially designed for any complex non-linear data. Initially, CNN was used in the image processing domain; presently, its application considered in many fields, like computer vision, speech processing, etc. Cai et al. (2020) presented a stacked LSTM based hybrid system for tool condition monitoring. Feature extraction was performed by stacked LSTM model from the vibration signals of the tool. For validating the model, authors used NASA Ames milling and 2010 PHM data challenge datasets. Outstanding performance was obtained from this model in tool wear prediction and hence the model is used when experiments run under many operating conditions. Guo et al. (2016) proposed a deep CNN based fault diagnostic algorithm for bearing diagnosis. This method comprises three convolutions layer, three pooling layers and one fully connected layer at the top of the model as a classifier. The deep learning approaches accomplished great success in the field of fault diagnosis of the rotating component.

CNN with residual learning and LSTM achieved great success in fault diagnosis and the vanishing gradient problem addressed during training. CNN model gives better classification accuracy with more layer. However, after reaching deeper in CNN network performance gets degraded due to the gradient problem. Thus, attaining much deeper deep learning network is harder to train. The residual learning block introduced to train network and easy to reformulate NNs layers in terms of residual function with input layer and it avoids gradient explosion problem. In present study, 1D time-series data and LSTM techniques were considered. LSTM architecture provides longer-term dependencies and can add or remove information from the cell regulated by gates, thus providing better classification accuracy.

2.10 MOTIVATION FROM THE LITERATURE

Literature review concludes that condition monitoring is a significant technique for fault diagnosis of rotating machine components and used for detecting early faults in the machines to avoid severe failure of machine during the working condition. Condition monitoring techniques are applicable in industries to monitor heavy machines to avoid downtime by notifying various vibration and temperature variation of machines. In machines and any mechanical structural failure is due to vibration of machine components. To avoid damages and failure of structures in machine component many researchers have worked on early fault detection in structure and machineries. In case of IC engine or rotating machines failure arises primarily by defect in ball bearing and defect in transmission gear unit. Even though many researchers worked on fault diagnosis of mechanical gear box and electrical induction motor. A lot of investigations are still possible in IC engine fault diagnosis using different monitoring techniques. Many numbers of techniques can be used for condition monitoring of IC engine considering combustion and loading unit. Most significant approach for condition monitoring is vibration analysis, which permits differentiating healthy and faulty engine components.

Vibration analysis involves time domain or frequency domain which can provide only information regarding past conditions of defective components of the engine. The concept can be extended with an advanced signal processing technique, machine learning techniques and deep learning approaches for developing online condition monitoring of the IC engine to identify different conditions of ball bearing and gear. Performance of monitoring technique in fault diagnosis depends on the classifier used for classification. Still many investigations are possible in finding best classifier. Many investigations are possible in building on-line fault diagnosis system using vibration signals with data mining techniques. In this research work, vibration signals of healthy and simulated faulty conditions are acquired which are used for offline monitoring using signal processing techniques and online condition monitoring of IC engine using machine learning and deep learning techniques.

2.11 OBJECTIVES

Condition monitoring of IC engine gearbox will be carried out using vibration analysis. In order to accomplish fault diagnosis of IC engine it is essential to fix number of major objectives.

The main objectives for proposed work are;

1. To investigate bearing faults of two stroke IC engine gearbox using vibration analysis through signal processing and machine learning techniques.
2. To build a four stroke IC engine setup with combustion process and loading system (Eddy current dynamometer) for condition monitoring of IC engine through vibration analysis.
3. To investigate faults in components of gearbox of an IC engine such as bearings and gears using signal processing techniques.
4. To diagnose faults of bearings and gears of gearbox of an IC engine based on vibration signals through machine learning approach.
5. To develop a deep learning model for diagnosis of bearing and gear faults in the gearbox of an engine.

2.12 SCOPE OF RESEARCH WORK

The scope of the current research work is drawn as follows;

- Fault diagnosis of ball bearing of two stroke IC engine gearbox using vibration signals is studied using signal processing and machine learning techniques.
- In the present work, experiment will be carried out on gearbox of four stroke IC engine with combustion and loading arrangement using eddy current dynamometer under different conditions of the engine.
- Investigation and fault identification of the basic components of gearbox like roller ball bearing and gear based on vibration signal analysis.

- Fault diagnosis of IC engine using conventional signal processing techniques such as time domain, spectrum, cepstrum, STFT and wavelet transform under various conditions of engine components.
- Machine learning techniques such as SVM, random forest and K star are used for classifying the features in order to diagnose the gearbox conditions.
- Determination of best feature and classifier combination for diagnosing the gearbox of an IC engine in two stroke and four stroke IC engine.
- Use of deep learning techniques such as CNN, residual learning, stacked LSTM methods for automatic feature extraction and classification of gearbox conditions.
- The study is to identify the most effective condition monitoring technique for predicting gearbox conditions more accurately while decreasing the error rate.

2.13 SUMMARY

This chapter discussed a review of existing gearbox condition monitoring techniques. Literature was primarily divided into categories on the monitoring of IC engine, gearbox elements such as gear and bearing condition monitoring using recorded signals. Also, applications of signal processing techniques and machine learning technique are discussed with respect to different mechanical systems. Advanced deep learning techniques are also discussed with respect to rotating machineries. Along with the above, an overview of each application method is discussed, citing many researchers who have successfully implemented these techniques for their respective area of research. In addition, this chapter discussed the objectives and scope of the current research work. Chapter 3 discusses the methodology and experimental approach used in this research.

CHAPTER 3

METHODOLOGY AND EXPERIMENT DETAILS

3.1 INTRODUCTION

This chapter describes the methodology involved in achieving the objectives of this research work. For performing fault diagnosis of the gearbox, a two-stroke and a four-stroke IC engine have been chosen. Experiments were conducted on a two-stroke engine gearbox which was cranked by a motor without applying load. In the four-stroke engine, a test rig was established to conduct experiments in actual running condition with loading arrangement by Eddy current dynamometer. The gearbox runs at various loading conditions. Finding faults is very difficult in the system. Hence, a physical parameter such as vibration has to be used for the diagnosis of faults.

3.2 METHODOLOGY

The proposed research work involves three stages. They are as follows:

(1) Fault detection based on signal processing techniques
(2) Fault diagnosis using machine learning approach
(3) Fault diagnosis using deep learning approach

Monitoring of gearbox is basically divided into two types (i) offline monitoring and (ii) online monitoring. Offline monitoring of the IC engine gearbox is based on signal processing techniques. Online monitoring of the IC engine gearbox is based on machine learning and deep learning approaches. These methods are discussed in the next sections. Figure 3.1 shows the methodology followed in monitoring system for fault diagnosis of gearbox in two stroke IC engine gearbox. Figure 3.2 shows the methodology followed in monitoring system for fault diagnosis of gearbox in four stroke IC engine gearbox.

3.2.1 Fault detection based on signal processing techniques

Analysis of the gearbox of an IC engine will be carried out using vibration signals from the set of experiments. Vibration signals carry information about the rotating components of the gearbox as they bear external applied load. The signal processing techniques, viz; time domain, spectrum technique, cepstrum technique, short time Fourier transform (STFT) technique and continuous wavelet transform (CWT) technique are employed for analyzing the vibration signals. The aforementioned techniques are an effective approach for detecting and diagnosing the faults of gears and bearings in the gearbox. The detailed description about the signal processing techniques is explained in the chapter 4

3.2.2 Fault diagnosis using machine learning techniques

Machine learning (ML) is the use of computer algorithms that improve and become more efficient by gaining and applying knowledge through repeated exposure to data. ML uses its own experience rather than explicitly programmed instructions. The collected signals such as vibration signals will be processed and analysed to diagnose the condition of the gearbox through ML technique. These algorithms build a model based on the input data, which is called training data and is used for future prediction. Continuous monitoring of gearbox signals provides early warning of the faults arising in the system, in order to avoid unplanned downtime of machine cost and time.

From literature study, it is understood that ML techniques are quite helpful in developing automatic diagnosis models for gearboxes. In online monitoring, ML techniques are used to classify the vibration signals of an IC engine into healthy and faulty conditions of gearbox components. ML mainly involves three stages; (i) feature extraction, (ii) feature selection and (iii) feature classification. In the present study features such as statistical, empirical mode decomposition (EMD)and discrete wavelet transform (DWT) are extracted from the vibration signals. Decision tree technique is used to select most important feature for classification. Support vector machine (SVM), Random Forest (RF) algorithm and K star algorithm are employed as classifiers. The details of ML techniques are described in chapter 5.

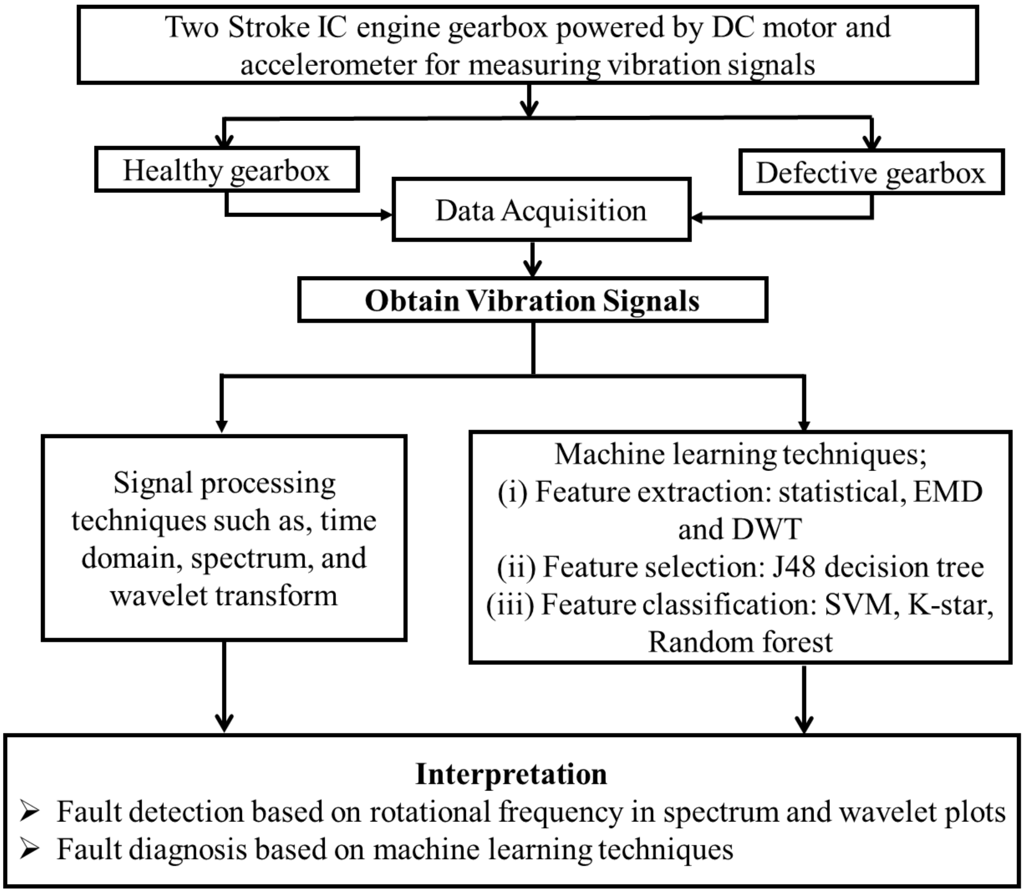


Figure 3.1 Methodology of Two stroke IC engine gearbox fault diagnosis

3.2.3 Fault diagnosis using deep learning techniques

DL is a class of ML techniques that uses multiple layers to progressively extract higher-level features from the raw input. In the field of DL, convolutional neural network (CNN) is feedforward network that outperforms others when it comes to generalizing and training networks with complete connectivity across adjacent layers. A CNN's architecture is composed of several stages. Each stage serves a distinct purpose. Each role is automatically filled by the algorithm. Each CNN architecture has four characteristics: multiple layers, pooling/subsampling, shared weights and fully connected layers. In the present study, CNN with residual learning, softmax function and long short-term memory (LSTM) are used for diagnosing the gearbox faults in four stroke IC engine. The acquired vibration signals of bearing and gear from four stroke IC engine gearbox are given as input to the CNN and classification is performed. The more details of the DL models are discussed in chapter 6.

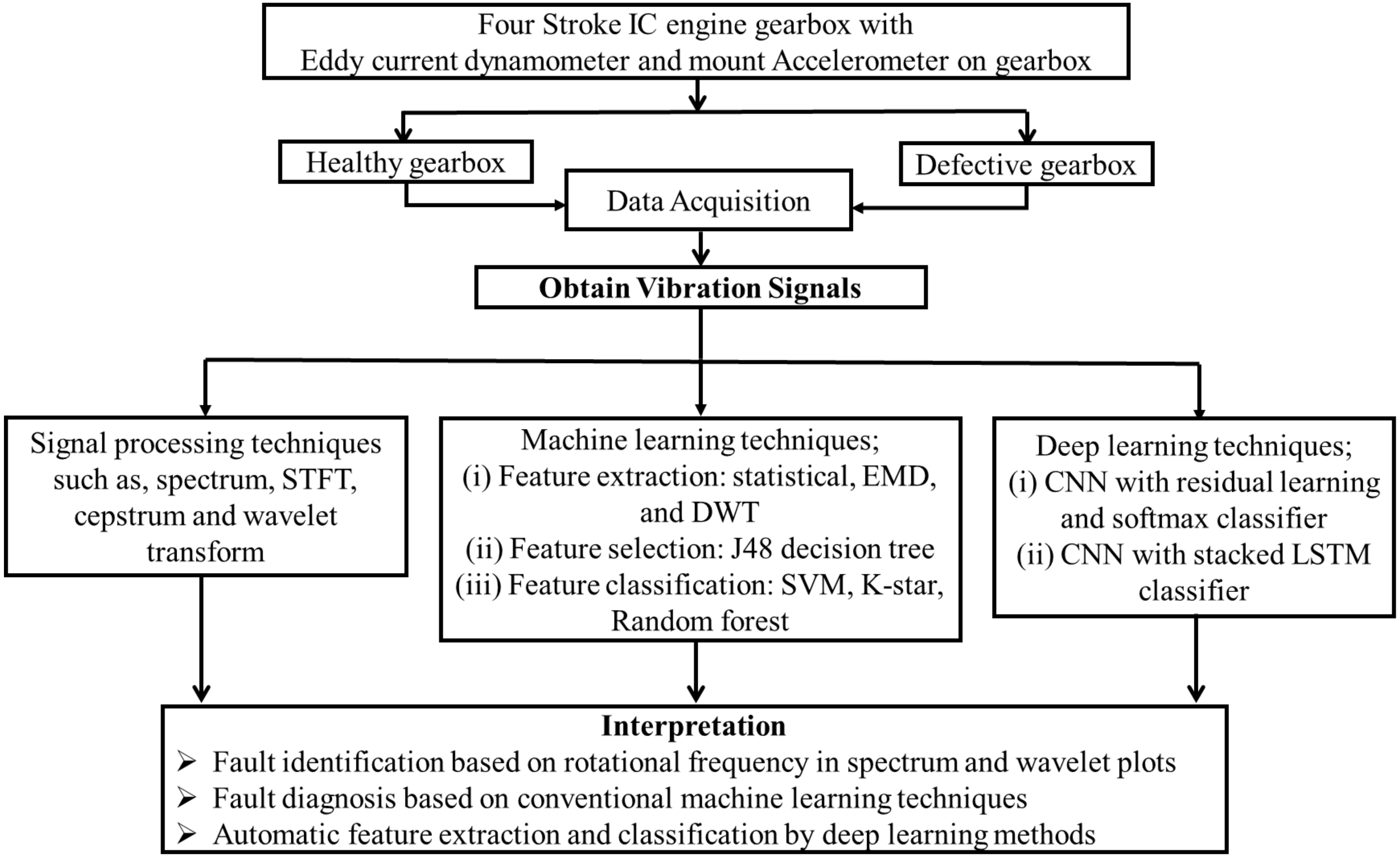


Figure 3.2 Methodology of Four stroke IC engine gearbox diagnosis

3.3 EXPERIMETNAL SETUP

In order to meet the objectives of this research work, it is essential to set up an experimental test rig to conduct the experiments. In this study, gear and bearing faults of a gearbox are considered to find the fault detection based on signal processing techniques and machine learning approach. Experiments are conducted on gearbox of a two-stroke motorcycle engine to diagnose the bearing faults without considering load and combustion. Then, experiments were carried out on a four-stroke single cylinder spark ignition engine, to diagnose gearbox faults such as gear and bearing.

The following sections discuss the details of the experimental test rig and procedures involved in the experiments.

The experimental test rig consists mainly of 2 major equipment:

- ➢ Two stroke single cylinder engine driven by a motor
- ➢ Four stoke single cylinder SI engine with Eddy current dynamometer

3.3.1 Experimental set up of two stroke IC engine without combustion and without loading arrangement

Experiments were conducted on a two stroke IC engine gearbox without combustion and loading for fault diagnosis of ball bearings using vibration signals under healthy and simulated faulty conditions. The schematic view of two stroke engine setup is shown in Figure 3.3. DC motor is attached to output shaft of the gearbox to power the crank and a dimmer-stat is used for controlling the voltage supply for the motor.

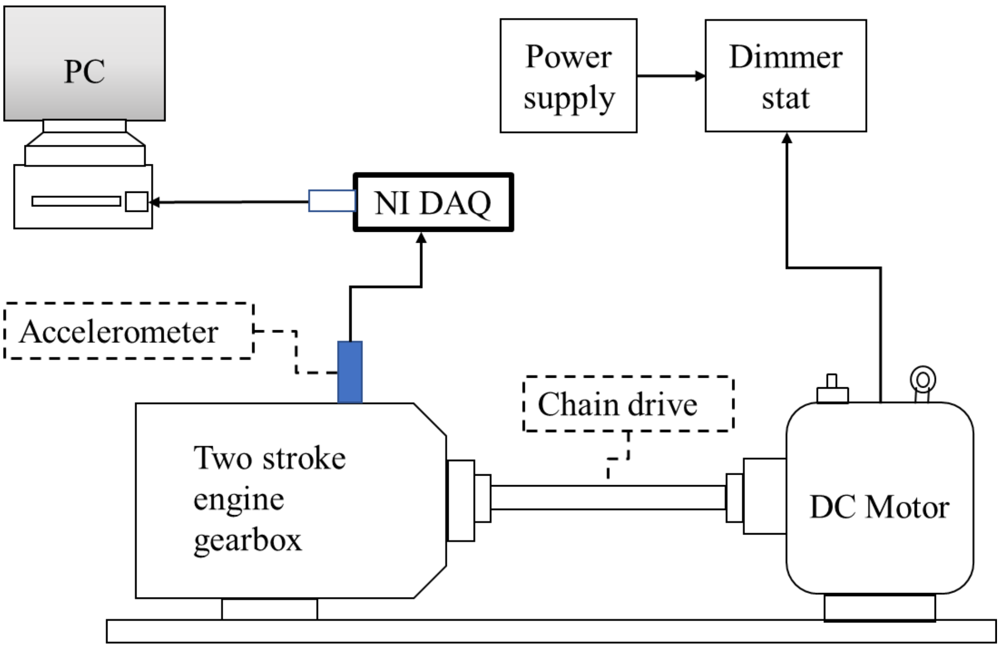


Figure 3.3 Schematic of two stroke engine test setup

The experiment is conducted at a constant crankshaft speed of 1600 rpm. Vibration signals are acquired using an accelerometer during engine running condition. Then, the analog signal is converted to digital by a DAQ (NI 9234) system with a sampling rate of 25 kHz and these signals are saved in PC and processed in LabVIEW for further analysis. Figure 3.4 shows the physical test set up of two stroke engine gearbox.

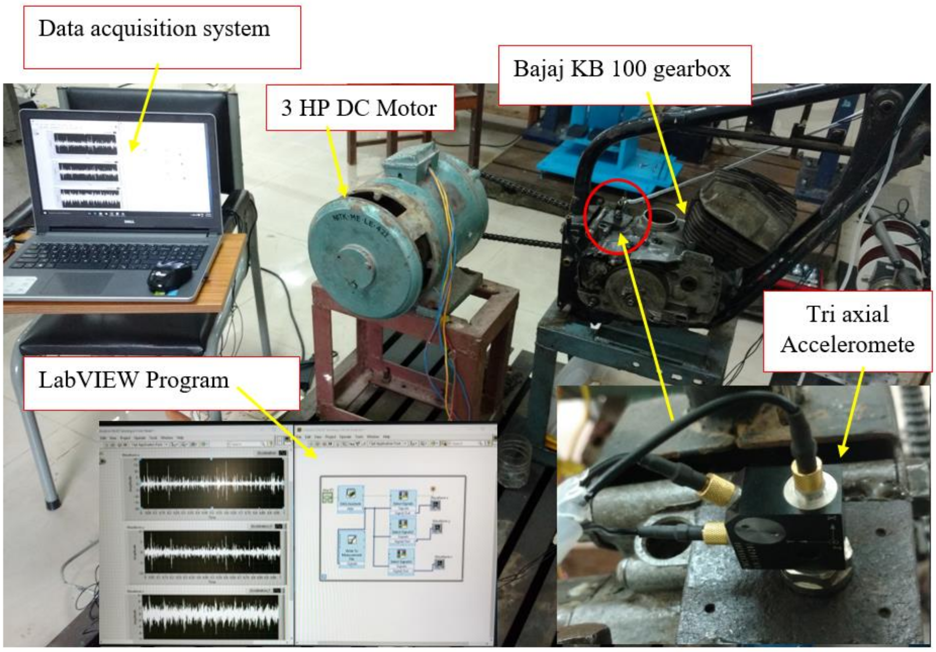


Figure 3.4 Experimental test rig for two stroke IC engine gear box

The vibration signals of the engine gear box are acquired for healthy and different simulated faulty conditions of roller ball bearing. The experiment is conducted for healthy and four simulated faulty conditions of the bearing, namely;

a. Inner race defect
b. Outer race defect
c. Ball defect
d. Combined faults of inner and outer race of bearing

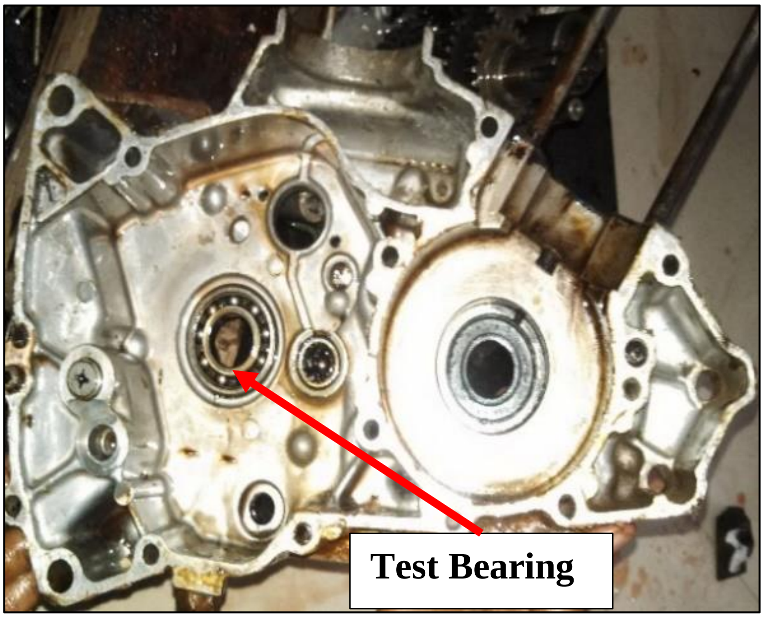
A total of 150 vibration samples are collected, out of which 30 samples for healthy and remaining signals are for each of the faulty conditions of the bearing. The data are stored in the computer for further analysis. In occurrence of inner race fault while transmitting impulses to outer surface area of casing, inner race defect had more transfer segments.

Table 3.1 Condition of ball bearing

Cases	**Nature of fault**	**Samples collected**
a	Healthy	30
b	2.5 mm inner race defect	30
c	1.5 mm outer race defect	30
d	2.5 mm inner and outer race	30
e	2 mm ball defect	30

In general, these impulses are weak in vibration signals and are difficult to find out. Therefore, analysis of inner race fault is very difficult (Lin and Qu 2000). Therefore, to understand inner race defect, a hole of 2.5 mm was drilled on it. Different conditions of ball bearing are shown in Table 3.1 for fault diagnosis of bearings.

IC engine.



(a)

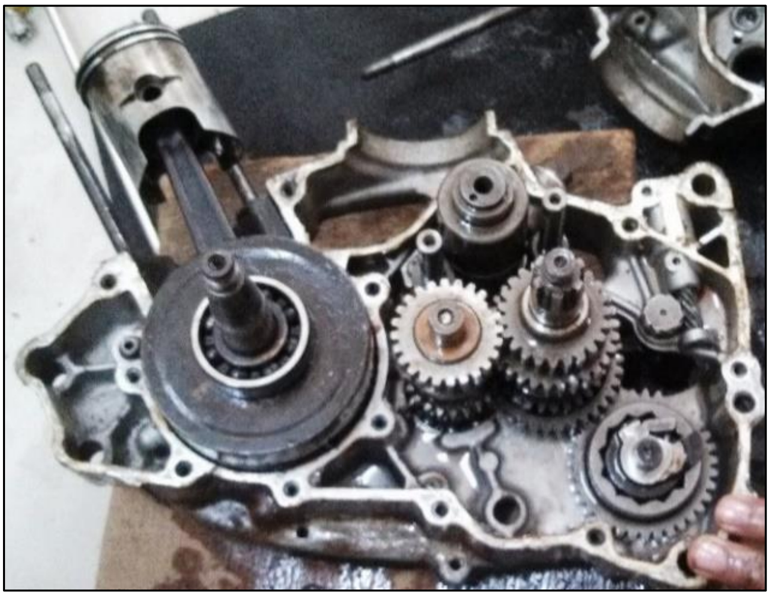


Figure 3.5 Two stroke IC Engine test gear box (a) Testing bearing location; (b) Sectioned view of engine gearbox

Figure 3.5 shows the sectioned view of engine and location of bearing in the gear box. Table 3.2 gives the specification of ball bearing used for fault diagnosis in the IC engine.

Table 3.2 Bearing specification of the test rig

Bearing parameter	**Value**
Outer race diameter (mm)	42
Inner race diameter (mm)	20
Ball diameter (mm)	6.3
Pitch diameter (mm)	31.5
Number of balls	9
Contact angle (°)	0(assumed)

3.3.2 Experimental setup of 4 stroke IC engine with combustion and eddy current dynamometer

Schematic representation of experimental setup consists of a four-stroke single cylinder IC engine with an eddy current dynamometer attached to it for applying load and a data acquisition system as shown in Figure 3.6.

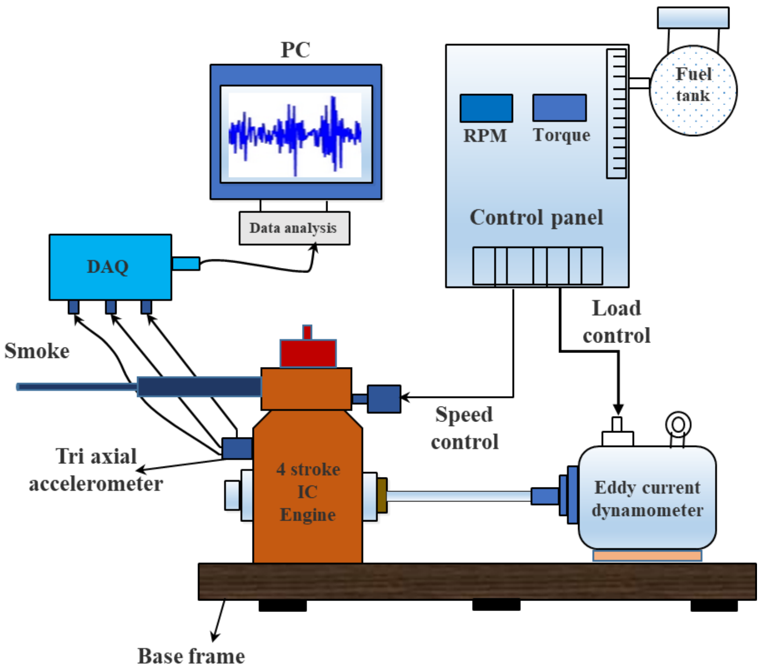


Figure 3.6 Schematic diagram of 4 stroke IC Engine setup using vibration signals

Experiments are conducted on a 4-stroke single cylinder twin spark ignition (SI) engine under its actual running condition. The specifications of the engine used in the test is shown in Table 3.3. The applied load to engine is controlled using an eddy current dynamometer having a capacity of 7.5 kW, which is coupled with the output shaft of the engine through a chain drive. It is equipped with variable electromagnets to change the magnetic field strength to control the amount of load applied. Speed of the engine during the test was maintained constant by keeping crankshaft rotational speed at 4300 rpm in 2nd gear position.

Table 3.3 Test engine specifications

Engine parameter	**Particulars**
Type of engine	DTS-I, 4-stroke, natural air cooled
Torque	10.8 Nm @ 5500 rpm
Displacement	124.6 cc
Power	11 bhp @8000 rpm
Number of gears	Five

Figure 3.7 shows the complete experimental set up with a data acquisition system for acquiring the vibration signals from the engine gearbox. The experiment is conducted for healthy gearbox condition and each defective condition of gear wheel one after the other by replacing and reassembling the gear specimen.

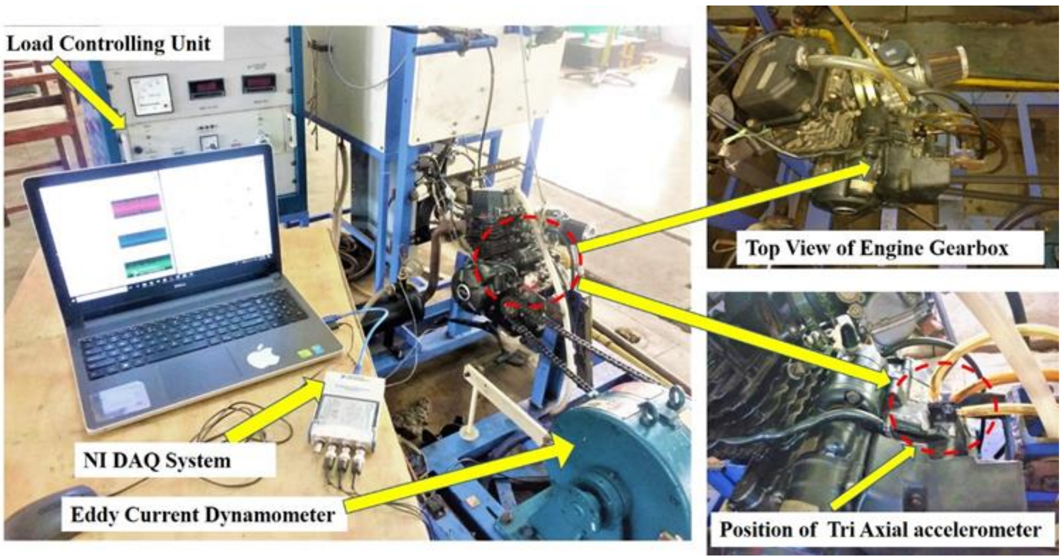


Figure 3.7 Test rig of 4-stroke IC engine

The position of defective gear in the engine primary shaft is displayed in opened view of gearbox in Figure 3.8.

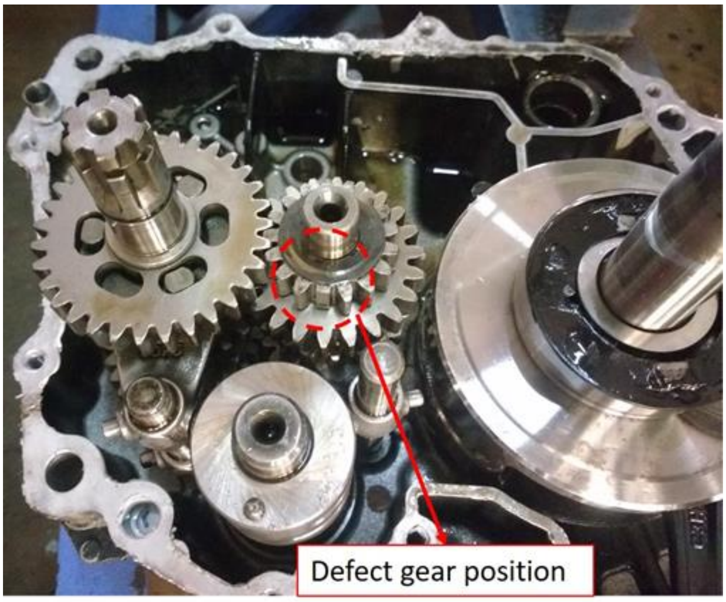


Figure 3.8 Inside view of engine gearbox

Similarly, experiments are conducted for healthy and defective conditions of ball bearing. The position of test bearing in the engine is displayed in opened view of gearbox in Figure 3.9.

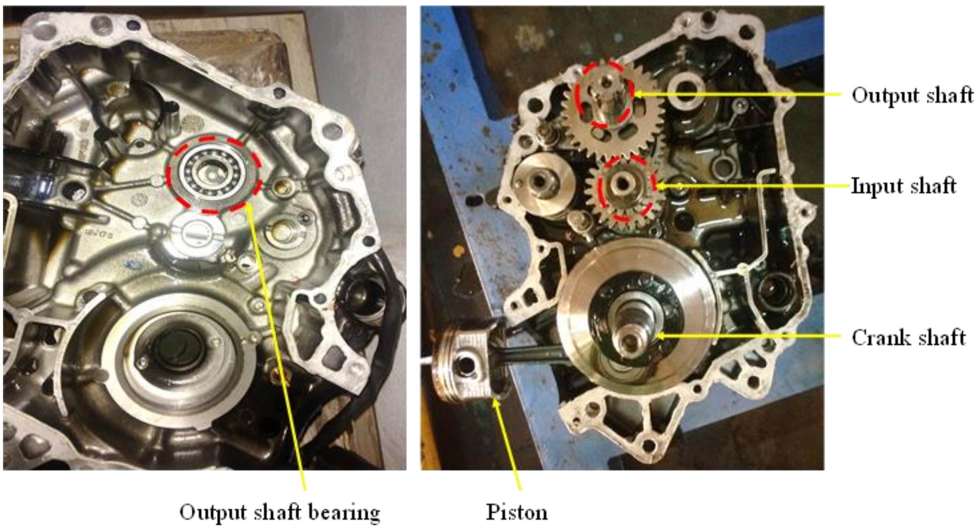


Figure 3.9 Location of test bearing in engine gearbox

3.3.2.1 Experimental procedure

a. The condition of the engine was confirmed to be good before the test by inspecting its various machine components, particularly engine gearbox parts.

b. In this experiment, the vibration signal was acquired from engine gear box for different condition of gear at constant crank shaft speed of approximately 4300 rpm at 2^{nd} gear position.

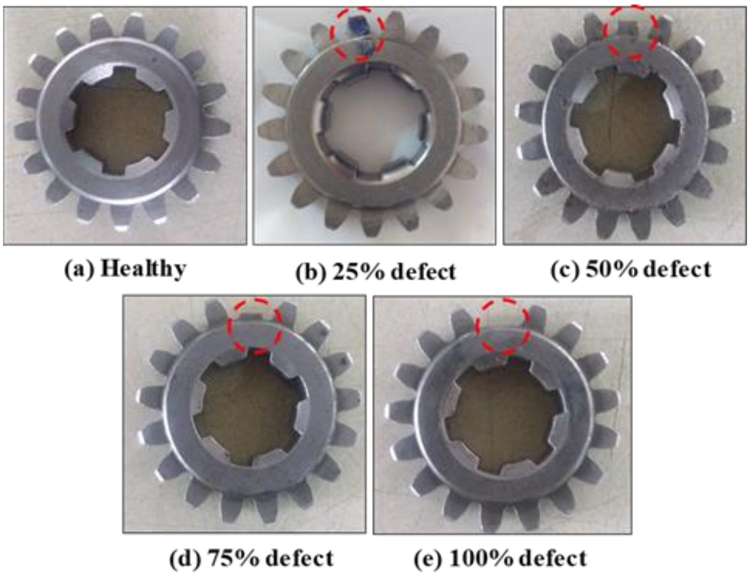


Figure 3.10 Different conditions of the gear (a) Healthy, (b) 25% defect, (c) 50% defect, (d) 75% defect, (e) 100% defect

c. In case of gear, artificial defect was introduced by machining the gear tooth progressively with 25%, 50%, 75% and 100% (one tooth removal) of the tooth face height as shown in Figure 3.10. The different conditions of gearbox used in this experiment are shown in Table 3.4.

d. In case of bearings, artificial defects were made on bearing surface, such as inner race defect, outer race defect and combined defects at inner and outer race as shown in Figure 3.11.

Figure 3.11 Ball bearing conditions used in the GB (a) Healthy, (b) Spall at inner race, (c) Spall at outer race, (d) Combined defects at inner and outer race

e. Test was conducted at three different loading conditions such as no load, half load and full load condition by the applying torque on the gearbox using eddy current dynamometer.

Table 3.4 Different conditions studied on engine gearbox fault diagnosis

Test No.	Condition of gear tooth and ball bearing	Engine gearbox condition
1	Normal	Healthy
2	One mm tooth thickness removal	25% defect
3	Two mm tooth thickness removal	50% defect
4	Three mm tooth thickness removal	75% defect
5	Four mm tooth thickness removal	100 % defect
6	2.5 mm defect at inner race	Spall at inner race
7	1.7 mm defect at outer race	Spall at outer race
8	2.5 mm defects at inner and outer race	Combined defects at inner and outer race

For acquiring the vibration signals, a piezoelectric accelerometer (Model-IEPE YMC 145A100, sensitivity-104.6 mV/g, Range- ±50g, Temperature- -41 to 121 ˚C, Response frequency>15 kHz) was mounted over the engine gearbox casing.

National Instruments hardware and LabVIEW 14 software were used for data acquisition and analysing the vibration signals. NI DAQ 9234, four channel, ±5 V, 24-bit DAQ system was used with an accelerometer to acquire the vibration signals of the engine and stored in the system. In this study, all signals have been acquired at a rate of 25.6 kHz sampling frequency.

3.4 SUMMARY

The detailed overview of the research work and methodology adopted are discussed in first section of this chapter. Methodology involves three different approaches. First one is fault detection based on signal processing approach; second one is fault diagnosis based on machine learning approach and third one is deep learning applications in fault diagnosis of engine gearbox. Also, brief explanation about two stroke and four stroke engine gearbox test setups are discussed. The procedure involved in conducting experiments are also included with information of sensors and data acquisition systems used for the experimentation. In the subsequent chapters, above said methods have been applied to study fault diagnosis of gearbox.

CHAPTER 4

FAULT DIAGNOSIS OF IC ENGINE GEARBOX USING SIGNAL PROCESSING TECHNIQUES

4.1 INTRODUCTION

Condition monitoring of IC engine gearbox based on vibration signal processing is an attractive research area (Peng et al. 2013). Vibration signal analysis using signal processing technique is extensively used for condition monitoring of rotating machinery systems (Jena et al. 2013; Rq et al. 2014). The purpose of this chapter is to study the fault diagnosis of IC engine gearbox using vibration signals and signal processing techniques. Vibration signals from the gearbox are acquired for healthy and induced faulty conditions of the gear and bearing. Experiments are conducted on ball bearing of two stroke IC engine gearbox without considering combustion and load. Then experiments are conducted on driving gear of four stroke IC engine gearbox with combustion and loading arrangement. The acquired signals are processed and analyzed using signal processing techniques. Spectrum, cepstrum, short time Fourier transform (STFT) and wavelet analysis are performed on acquired signals of the gearbox.

4.2 OFFLINE MONITORING OF IC ENGINE GEARBOX

In offline monitoring, different signal processing techniques were used for vibration analysis. The methods such as time domain analysis, spectrum analysis, cepstrum analysis, wavelet analysis are used in this present study and discussed briefly in the following subsection.

4.2.1 Time domain analysis

Time domain study gives the dynamic variation of vibration levels and the recorded data reveals amplitude variation with respect to time. It is very difficult to recognize the defective conditions of machine elements from time domain analysis. Root mean square (RMS) is a time domain feature, which gives information of the signal by taking mean average of the data points. For all the conditions RMS value is calculated and given in time domain plots.

4.2.2 Spectrum analysis

Fourier transform (FT) is used to obtain frequency information of vibration signals. A Fourier integral pair is given in equations (4.1) and (4.2).

$$f(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} F(\omega)e^{-j\omega t}d\omega \quad (4.1)$$

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t}dt \quad (4.2)$$

In equation (4.2), F(ω) is the FT of the signal *f(t)*. The FT is appropriate for analyzing signals which are stationary and periodic in nature. Fast Fourier transform (FFT) is the advanced algorithm of FT and these techniques are used by many researchers in fault diagnosis of machinery components (Vernekar et al. 2014).

4.2.3 Cepstrum analysis

Cepstrum analysis is one of the nonlinear signal processing techniques used for identifying a family of harmonics in the spectrum of the gearbox signals. The cepstrum is defined as the inverse Fourier transform of the logarithm of the power spectrum and is called the spectrum of the spectrum. This approach has a variety of applications, such as in the field of speech and image processing. Recently, this approach has also been used in the area of fault diagnosis of machines using vibration signals (Zhang *et al.*, 2019).

The real cepstrum of the signal x(n) is given by equation (4.3) (El Morsy and Achtenová., 2014). Figure 4.1 depicts the relationship between the spectrum and cepstrum.

$$c_{real} = \frac{1}{2\pi}\int_{-\pi}^{\pi} \log\left|X\left(e^{j\omega}\right)\right| e^{j\omega n}d\omega \quad (4.3)$$

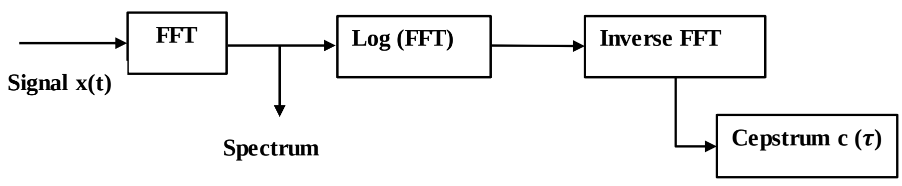


Figure 4.1 Relationship between spectrum and cepstrum

4.2.4 Short-Time Fourier Transform (STFT)

STFT is a time-frequency analysis technique which has the ability to analyze non-stationary signals by dividing them into small time-domain series of equal length through a windowing function. Then, by applying FT, the plots are obtained which give information about time and frequency at different positions. The STFT is performed to obtain information about time and frequency instantaneously by multiplying the window function by the time domain signal.

The STFT methods were followed for analyzing non-stationary signals *x(t)* by using equation (4.4) (Owens 1988).

$$STFT_X^W(\tau,\omega) = \int_{-\infty}^{\infty} x(t)W^*(t-\tau)e^{-i\omega t}\,dt \qquad (4.4)$$

In equation (4.4), *x(t)* is signal to be analyzed, ω is rotational frequency, W^* is a window function and τ is time variable. The difference between FFT and STFT can be observed by comparing equations (4.2) and (4.4), i.e., only in terms of window function. The performance of STFT depends on this windowing function (Moosavian et al. 2017). In the analysis, the hamming window function is used for getting time frequency information.

4.2.5 Continuous Wavelet Transform (CWT) Analysis

Wavelet analysis (Wang et al. 2011; Yan et al. 2014)is one of the important signal processing techniques in fault detection. This technique can be used for non-stationary signal analysis (Zheng et al. 2002). In wavelet analysis, the most important part is that it will give information about time and frequency simultaneously to understand signals in a better way. CWT is a more promising technique in the family of wavelet transforms. This will display the frequency information with respect to time along with amplitude variation. The plots obtained from the CWT are called spectrograms, which can be varied with different scaling parameters.

The CWT of time domain signal *x(t)* is given by equation (4.5);

$$CWT\ X_\psi(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt, \quad \{a,b\ \in R,\ \ a\neq 0 \qquad (4.5)$$

In equation (4.5), $\psi^{*}(t)$ is the complex conjugate of the analyzing wavelet, *'a'* is the scaling parameter, *'b'* is the translation parameter. $X_{\psi}(a,b)$ is a new transformed signal of function *'a'* and *'b'*. In the transformed signal, $\frac{1}{\sqrt{a}}$ is energy exhibition feature in wavelet transform and energy of signal is normalized by multiplying term $\frac{1}{\sqrt{a}}$ at each scale of individual wavelet constant (Wu and Chen 2006).

4.2.6 Morlet wavelet under CWT

The Wavelet family contains a very large number of different wavelets for different applications. In that, the Morlet wavelet belongs to the CWT family, which is suitable for analysis of non-stationary signals generated by vibrating machinery components. The mother wavelet of this is given by equation (4.6) (Zheng et al. 2002).

$$\boldsymbol{\Psi(t) = \frac{1}{\sqrt[4]{\pi}}\left(e^{j\omega_0 t} - e^{-\frac{\omega_0^2}{2}}\right)e^{-\frac{t^2}{2}}} \tag{4.6}$$

In equation (4.6), 'ψ' is mother wavelet, *'ω_0'* represents central frequency of the mother wavelet. The term $e^{-\left(\frac{\omega_0^2}{2}\right)}$ is used for fine-tuning non-zero mean of the complex sinusoid. It can be irrelevant when $\omega_0>5$. If $\omega_0>5$, the redefined mother wavelet is given in equation (4.7).

$$\Psi(t) = \frac{1}{\sqrt[4]{\pi}}e^{j\omega_0 t}\, e^{-\frac{t^2}{2}} \tag{4.7}$$

4.3 EXPERIMENTAL RESULTS OF TWO STROKE IC ENGINE GEARBOX

Vibration signals from the IC engine gear box under different conditions of ball bearing are investigated using various signal processing techniques such as; time domain, frequency domain and wavelet analysis. Experiments are conducted on ball bearing fault diagnosis of two stroke engine gearbox without considering external load. Vibration signals from the gearbox casing are acquired and analyzed. The result obtained from these methods are discussed in the following sections.

4.3.1 Time domain study and Spectrum analysis

Time domain plots of vibration signals under different conditions of ball bearing are plotted as shown in Figure 4.2. In time domain plots, it is very difficult to differentiate the nature of the bearing status because time domain plots convey the dynamic variation of vibration signals in terms of amplitude with respect to time. Also, it doesn’t provide any information about frequency component of the given signal.

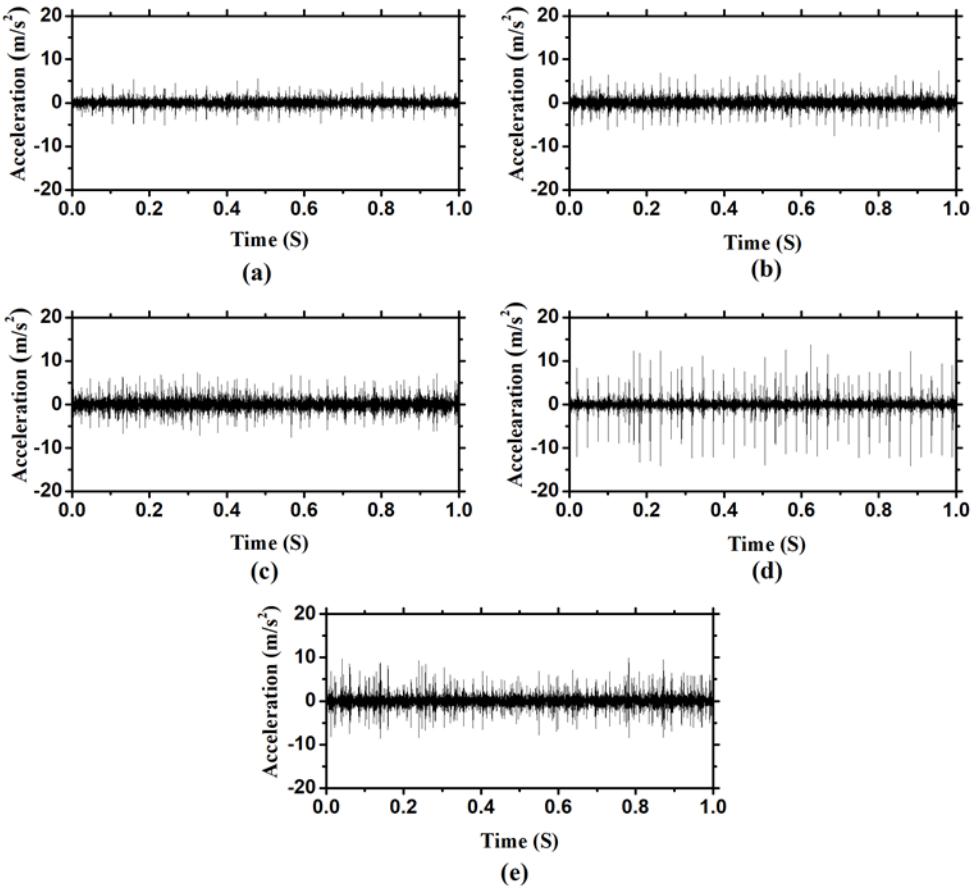
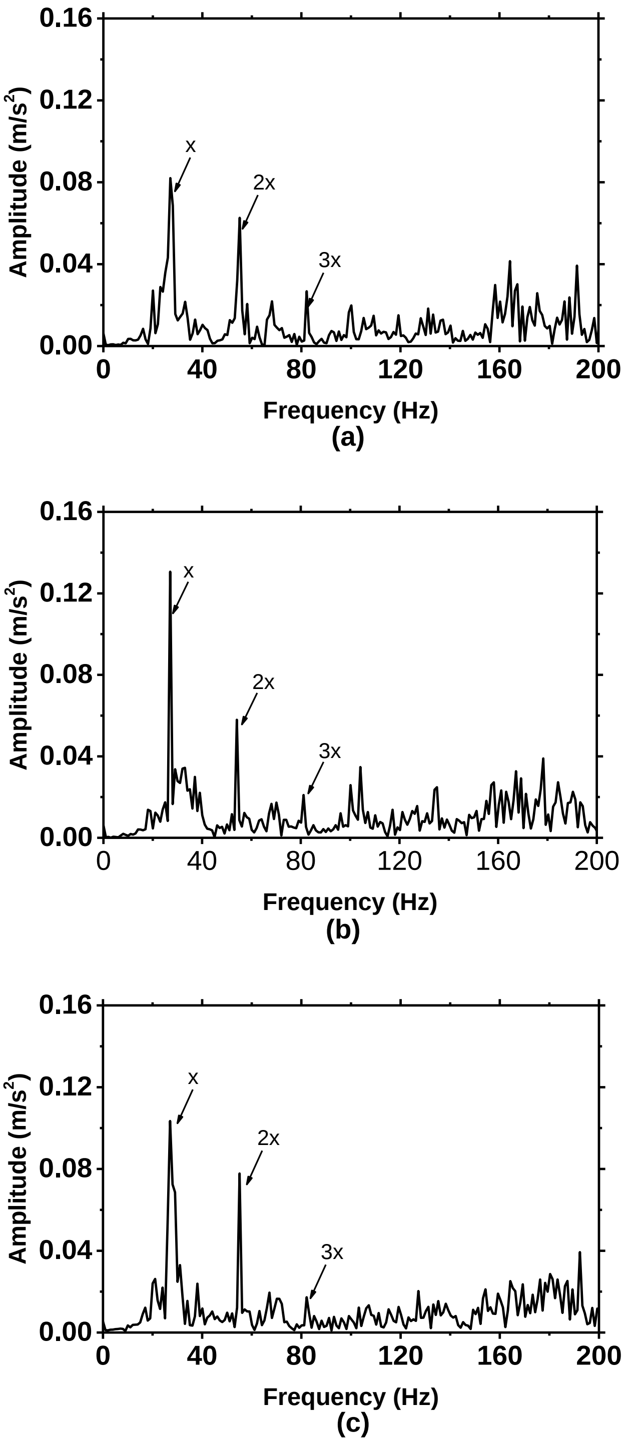
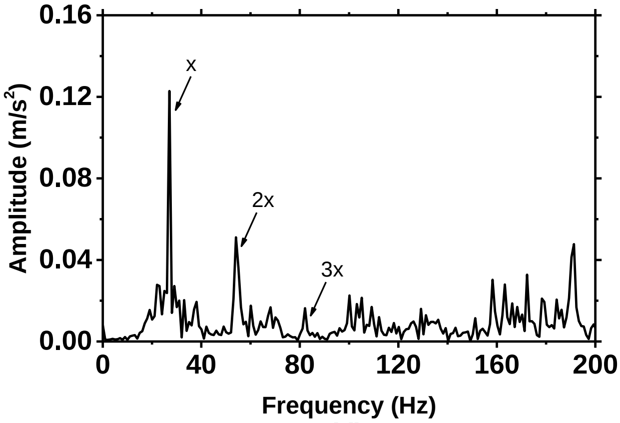


Figure 4.2 Time domain plots of bearing conditions of (a) Healthy, (b) Inner race defect, (c) Outer race defect, (d) Ball defect, (e) Inner and Outer race defect

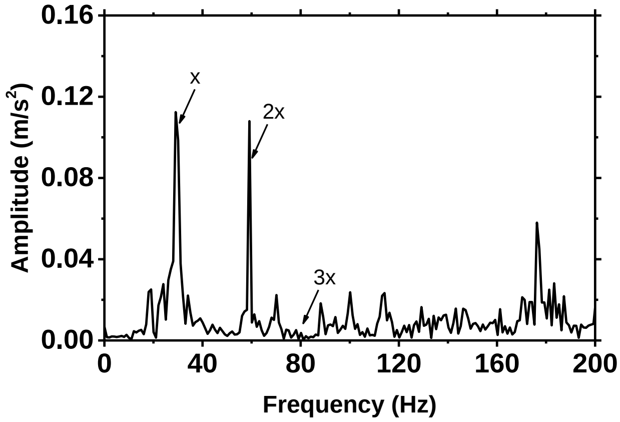
Figure 4.3 depicts the spectrum graphs of vibration signals under different conditions of the ball bearing. In IC engine gearbox, crankshaft rotational frequency is dominating all other components frequencies of the gearbox. The spectrum plots will show the nature of vibration signs of ball bearing under healthy and different induced faulty condition.

In IC engine gearbox vibration spectrum plots, the analysis bandwidth is limited to a range of 200 Hz, since the rotational frequency of crankshaft is 27 Hz and its harmonics can be detected within 200 Hz range. From Figure 4.3, for the different condition of bearing, peak frequency is observed at 27 Hz, 54 Hz and 84 Hz. These are first, second and third harmonics of crankshaft rotational frequency.





(d)



(e)

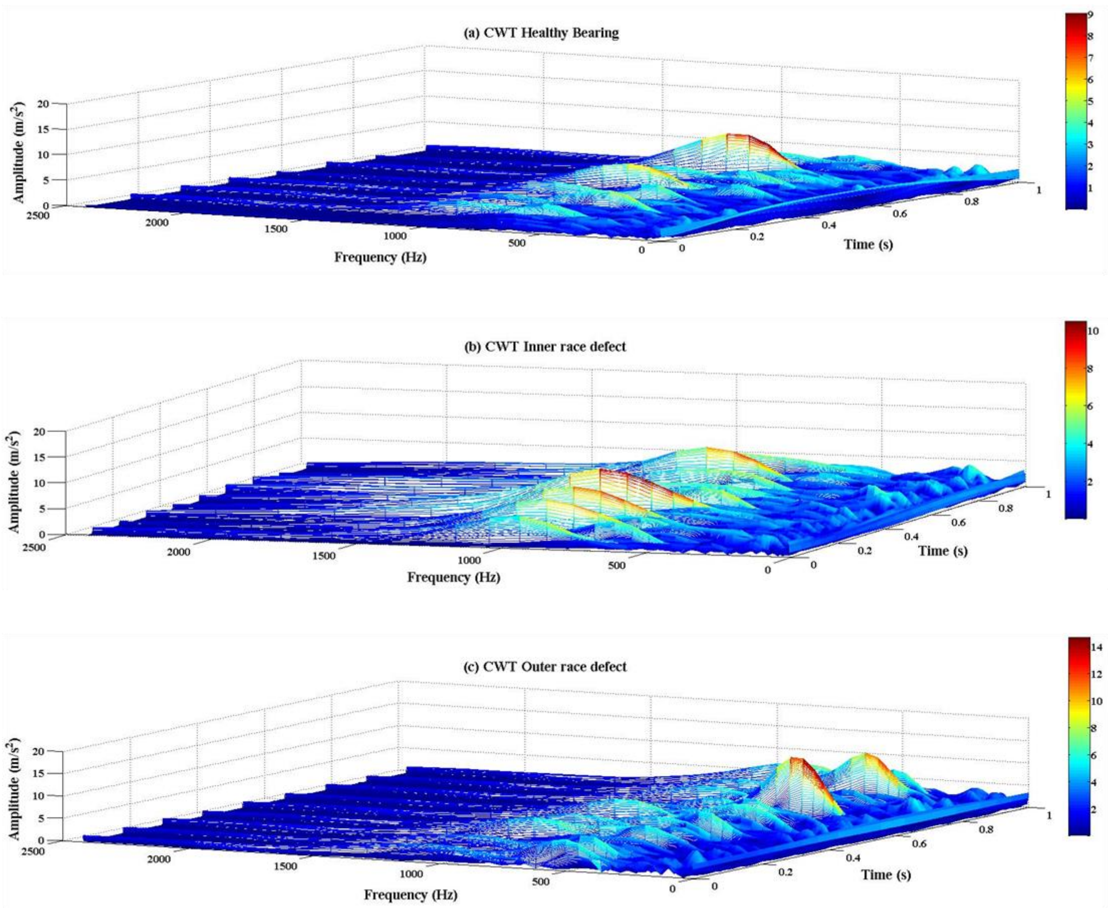
Figure 4.3 Frequency domain plots of bearing conditions of (a) Healthy, (b) Inner race defect, (c) Outer race defect, (d) Ball defect, (e) Inner and Outer race defect

For identifying the bearing condition, the amplitude of vibration of these harmonics is analysed. In healthy bearing condition, the peak amplitude of vibration is 0.08 m/s^2, where-as in inner race defect case the amplitude of vibration is 0.13 m/s^2 with respect to first harmonic(f_s). Similar increment in vibration amplitude can be seen in the outer race, ball defect and combined inner and outer race of bearing with respect to peak amplitude of vibration of healthy bearing condition.

4.3.2 CWT analysis

As seen from the Figure 4.4, one can say that there is a slight variation in the amplitude of fundamental crankshaft rotational frequency of about 27 Hz with respect to different conditions of the ball bearing. In addition to spectrum analysis, CWT technique is used to identify the conditions of IC engine. Figure 4.4 depicts the CWT plots of vibration signals under different conditions of ball bearing such as; (a) healthy, (b) inner race defect, (c) outer race defect, (d) ball defect and (d) inner and outer race defects.

From the CWT plots, a good amount of accuracy is seen in identifying the faults in terms of amplitude variation with respect to time frequency plots. In CWT plots, the amplitude variation at a frequency band of 500-1500 Hz corresponding to different conditions of ball bearing can be seen in Figure 4.4.



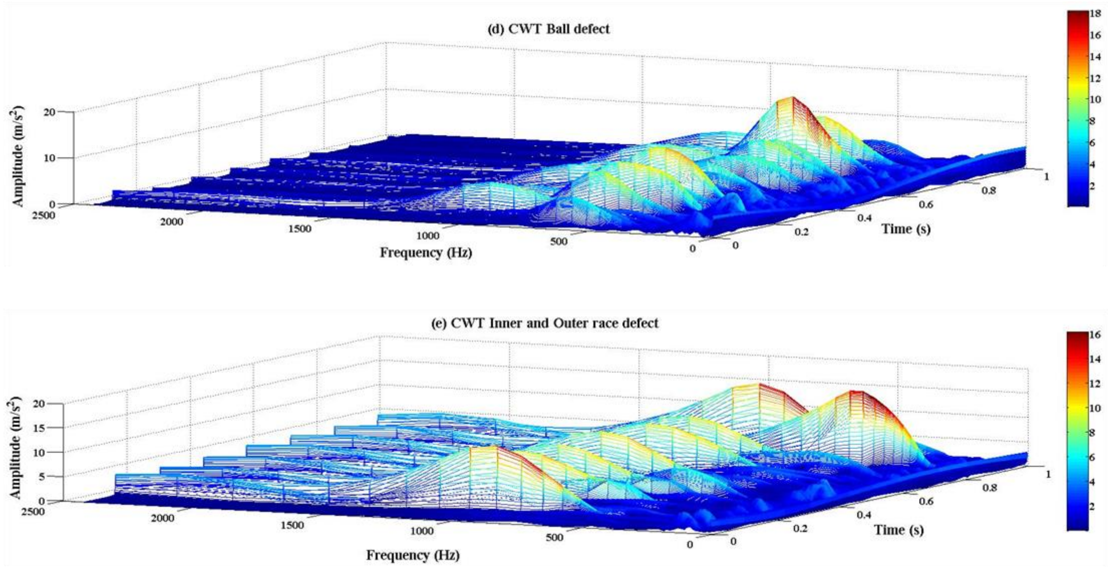


Figure 4.4 Continuous wavelet transforms plots of (a) Healthy condition, (b) Inner race defect, (c) Outer race defect, (d) Ball defect, (e) Inner and Outer race defect

Based on the above vibration analysis of a bearing, it can be seen that, even in the presence of a defect in the bearing, it is quite difficult to determine which frequency corresponding to a particular defective condition. The reason behind this is, the crank shaft rotates at a higher rate, which has the significant influence on the frequency spectrum of the gearbox, which is the dominant frequency among all others. As a result, when considering a component at the system level, it is difficult to detect component damage using vibration spectrum analysis. This can be overcome through the application of machine learning techniques.

4.4 EXPERIMENTAL RESULTS OF FOUR STROKE IC ENGINE GEARBOX

In this work, vibration analysis of four-stroke IC engine gearbox under real-time operating condition with different loading cases are studied. From the gearbox of the engine, vibration signals are acquired under healthy gear, 50% tooth defect and 100% tooth defect. These signals are studied with various signal processing techniques.

4.4.1 Time domain analysis

Figure 4.5 depicts the time domain plots of gearbox under no load conditions with healthy, 50% gear tooth defect and 100% gear tooth defect. In these plots, one can observe slight variation in amplitude in comparison with different load and cases of gear defects.

In Figure 4.5(a), for no load with healthy condition amplitude is very small (-5 m/s^2 to +5 m/s^2) whereas in Figure 4.5(b) and 4.5(c) for 50% defect and 100% defect respectively, the amplitude is slightly higher (-6 m/s^2 to +6 m/s^2) when compared to healthy. Impacts are very clear in 100% gear tooth defect condition.

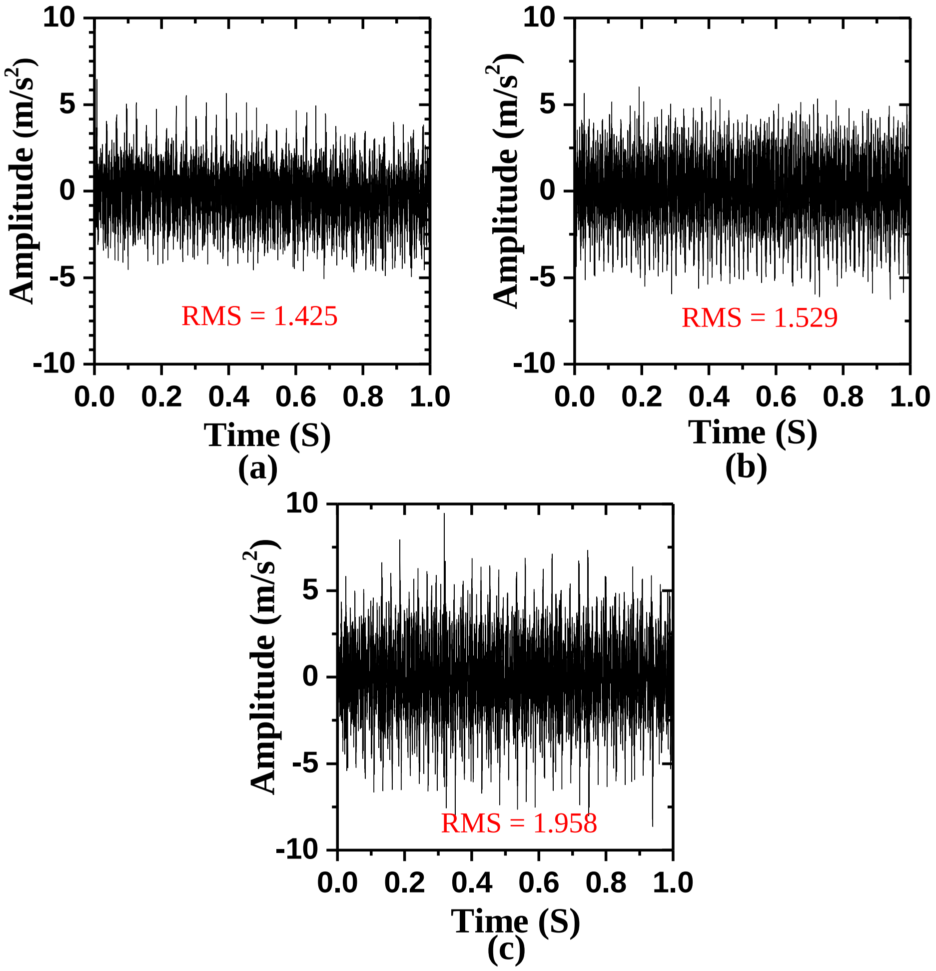


Figure 4.5 Time domain plots of no-load condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

Similarly, Figure 4.6 and 4.7 indicates time series plots for load1 and load2 condition. In comparison with healthy condition, variation of amplitude and impacts of defective gear were clearly indicated by 50% defect and 100% defect in increasing loading conditions.

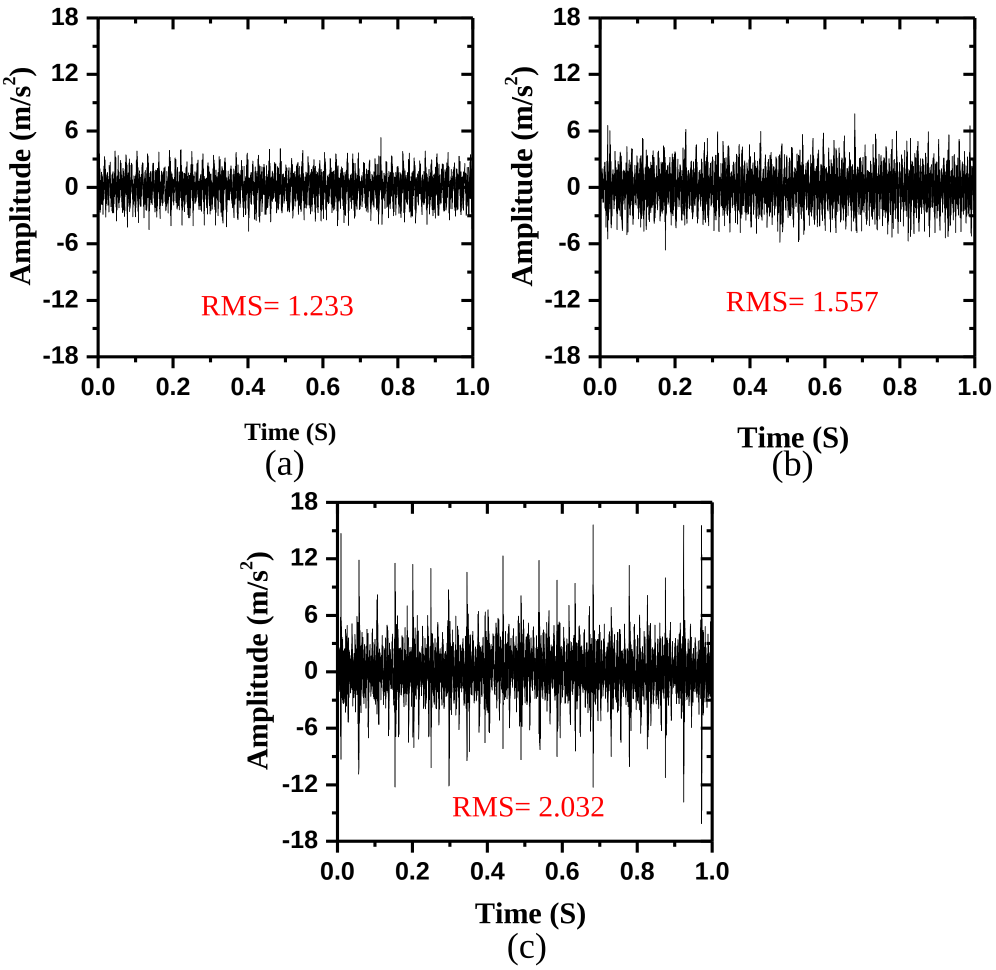


Figure 4.6 Time domain plots of load1 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

Even though time domain analysis gives time information with respect to various conditions of gearbox, identifying the severity of defect is difficult using it. For better understanding of conditions of gearbox, frequency information is needed and this can be done by spectrum analysis using FFT.

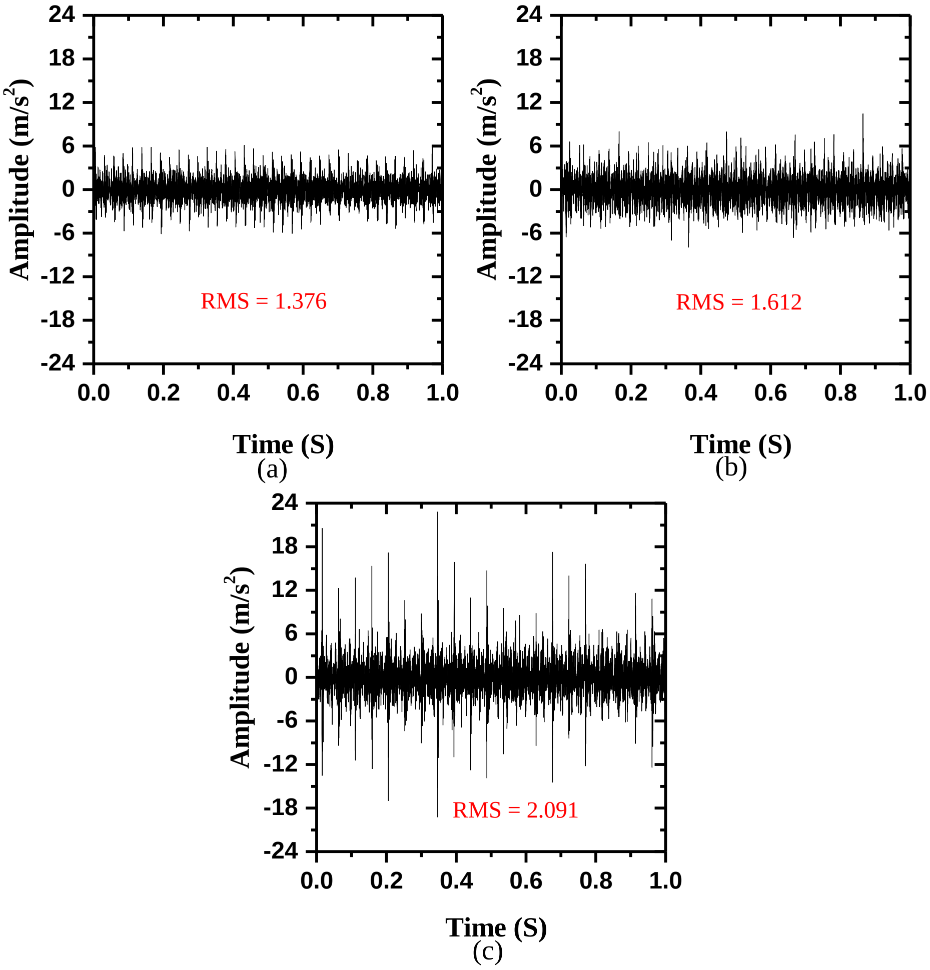


Figure 4.7 Time domain plots of load2 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

4.4.2 Frequency domain analysis

The information of frequency of gearbox components is obtained from FFT algorithm. In IC engine gearbox, the crankshaft rotational frequency (CRF) found to be dominating all other frequencies and the same can be noticed from spectrum plots in Figure 4.8, Figure 4.9 and Figure 4.10 for different load conditions of gearbox. These plots display the gearbox vibration signature for healthy, 50% defect and 100% defect conditions under varying load conditions with CRF and its harmonics (1X,2X,3X…. etc.,) and gear mesh frequencies (GMF).

In IC engine gearbox, the significant frequencies are CRF and GMF. Hence, spectrum plots of the gearbox show amplitude variation at these two frequencies and its harmonics. Table 4.1 shows gear ratios at different locations of the engine test rig. By using this gear ratio, engine rpm was calculated for comparing frequency component under different conditions of gearbox. GMF is calculated by equation (4.1).

$$\mathrm{GMF} = \mathrm{T_n} \times \mathrm{N} \tag{4.1}$$

where, 'T_n' is number of gear teeth and 'N' is rpm of gear.

Table 4.1 Gear ratio from dynamometer to engine

Location	**Gear ratio**
Dynamometer to output shaft of engine	42/14 (3.00)
Output to input shaft of engine	31/17 (1.824)
Input to crankshaft of engine	75/21 (3.571)

Table 4.2 shows GMF for no load condition (i.e., at zero torque). For different defect conditions, amplitude of GMF and CRF will be observed in the spectrum plots. GMF is one of important parameters for detecting fault in the gearbox. If broken tooth gear meshes with tooth of other driven gear, GMF will show indication by revealing its increase in amplitude and sideband around the GMF with respect to healthy gear.

Table 4.2 GMF at no load

Location	**Speed (rpm)**	**Frequency (Hz)**
Speed at dynamometer	220	3.6
Gear speed	660	11
Pinion speed	1204	20
Crankshaft speed	4300	72
Gear mesh frequency	20460	341

Table 4.3 shows GMF for load1 (at torque 9.6 Nm) and respective frequencies are tabulated at different positions of the gearbox using gear ratio. This torque has been applied from the eddy current dynamometer to the output shaft of an engine

Table 4.3 GMF at load1

Location	**Speed (rpm)**	**Frequency (Hz)**
Speed at dynamometer	215	3.58
Gear speed	645	10.75
Pinion speed	1176.5	19.6
Crankshaft speed	4201	70
Gear mesh frequency	19995	333

Table 4.4 displays GMF for load2 condition (at torque 13.3 Nm) and respective frequencies at different positions of the gearbox. At 0, 9.6 Nm and 13.3 Nm applied torque conditions the speed of the engine is observed as 4300, 4201and 4104 rpm respectively. The frequency corresponding to different load conditions are tabulated in Tables 4.2, 4.3 and 4.4.

Table 4.4 GMF at load2

Location	**Speed (rpm)**	**Frequency (HZ)**
Speed at dynamometer	210	3.5
Gear speed	630	10.5
Pinion speed	1150	19.2
Crankshaft speed	4104	68.4
Gear mesh frequency	19530	326

Figure 4.8 shows the spectrum plots for the no load condition. In Figure 4.8(a) for healthy condition, the 2X component of crankshaft rotational frequency amplitude is about 0.45 m/s^2. Whereas in case of Figure 4.8(b) and Figure 4.8(c) for 50% defect

and 100% defect case the amplitude of 2X component increased to 0.73 m/s^2 and 1.1 m/s^2 respectively. This indicates the presence of defects in the engine gearbox.

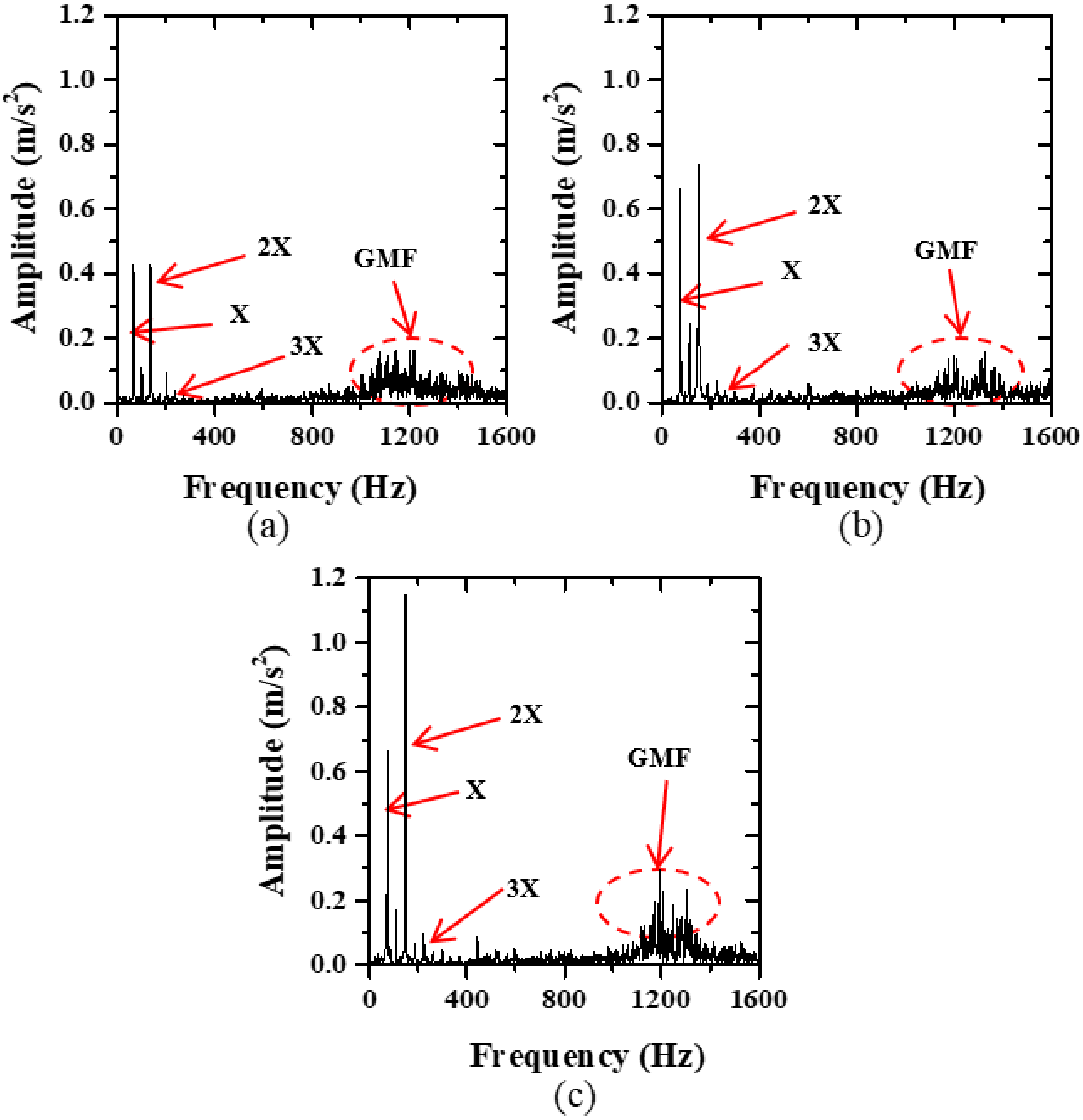


Figure 4.8 Spectrum plots of no-load condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

Similarly, the variation of GMF is also observed with respect to the frequency band of 1000-1300 Hz which is in the range of 3rd and 4th harmonics of GMF. In Figure 4.9(a), the GMF largest peak amplitude is around 0.15 m/s^2 for healthy gear and in Figure 4.9(b) and Figure 4.9(c) the GMF is increased to 0.19 m/s^2 for 50% defect and 0.27 m/s^2 for 100% defect respectively. This clearly indicates that, the gear box is having tooth defect in the running condition of gear. Similar variation of amplitude in case of load1 and load2 can be observed with respect to CRF with its 2nd harmonics and GMF in the band of 1000-1300 Hz.

Figure 4.9 illustrates the spectrum plots for load1 conditions. Spectrum plots exhibit increase in amplitude with increase in defect conditions for different conditions of the gearbox.

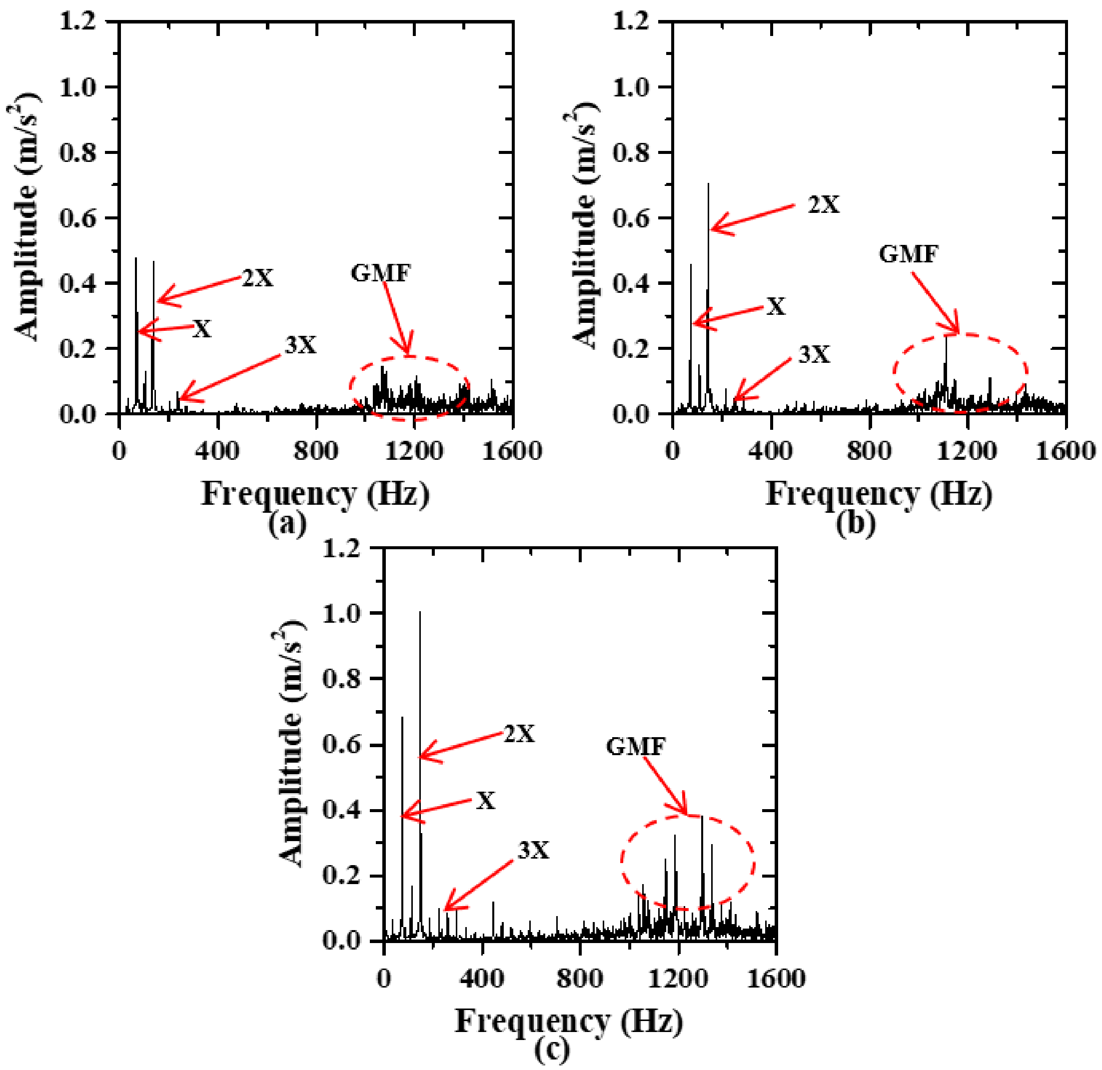


Figure 4.9 Spectrum plots of load1 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

Similarly, for load2 conditions, spectrum plots indicate same trend as the defect condition severity changes from healthy to 50% defect and 100% defect as can be observed from Figure 4.10.

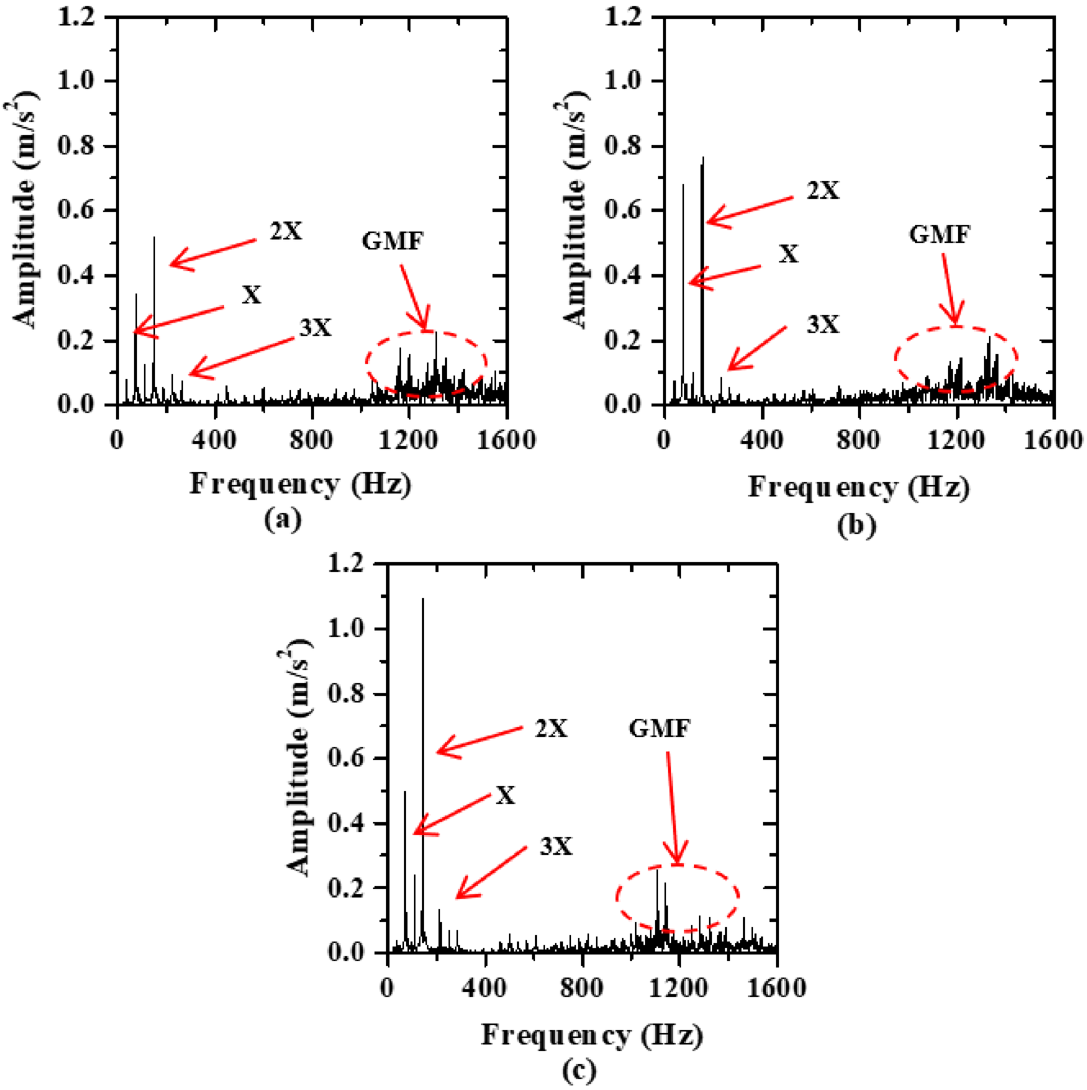


Figure 4.10 Spectrum plots of load2 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

Spectrum analysis provides information of frequency but there is a drawback that no information of time period is available in the FFT plots. For further detailed understanding other time frequency methods need to be studied. In next sub section cepstrum method is discussed for analyzing the gearbox conditions.

4.4.3 Cepstrum analysis

Cepstrum plots of IC engine gearbox under healthy, 50% defect and 100% defect with no load, load1 and load2 conditions are displayed in Figure 4.11, 4.12 and 4.13 respectively. Cepstrum plots indicate harmonics of dominant frequency and it is represented by quefrency with respect to amplitude variations for various gearbox conditions.

Figure 4.11 (a), (b) and (c) show cepstrum plots for no load condition for healthy, 50% defect and 100% defect of gear tooth respectively. As discussed in the spectrum analysis, GMF is in the range of 1000-1300 Hz which slightly alters due to variation in fuel and air mixture during combustion. In cepstrum analysis, the notion 'frequency' is replaced by 'quefrency' and it varies with respect to different conditions of the gearbox. In Figure 4.11(a) for no load with healthy condition, corresponding quefrency is about 0.0008203 sec, and it shows acceleration of the gearbox of about 0.06116 m/s^2 which is used as reference for finding faulty conditions of the gearbox.

As the condition of the gearbox is changed to 50% defect, quefrency is about 0.00078125 sec, and it indicates acceleration level of about 0.6973 m/s^2 which is shown in Figure 4.11(b). Similarly, for 100% tooth fault condition, quefrency is about 0.0007812 sec, and it shows acceleration level of about 0.09205 m/s^2 in Figure 4.11(c). This increase in amplitude at the dominant quefrency clearly implies that there is a fault in the IC engine gearbox. In cepstrum plots, along with dominant quefrency, its harmonics are also observed.

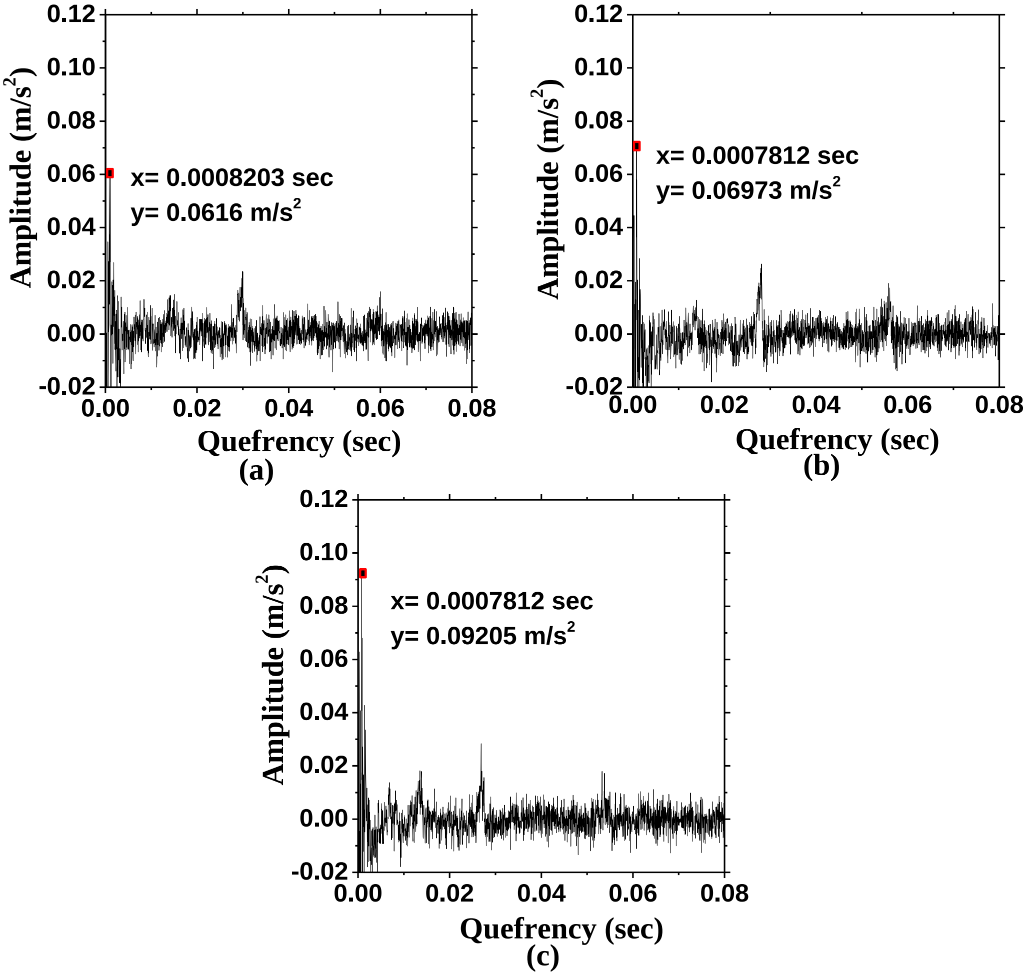


Figure 4.11 Cepstrum plots of no-load condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

Load1 and load2 cepstrum plots are also exhibiting same trend in increasing acceleration amplitudes with respect to quefrency of the gearbox. Figure 4.12(a) shows healthy condition under load1 with quefrency of 0.00070312 sec, and its corresponding acceleration level is about 0.0812 m/s^2. In case of 50% defect and 100% defect, quefrency is 0.00078125 sec and amplitude have increased to 0.08285 m/s^2 and 0.09697 m/s^2 respectively.

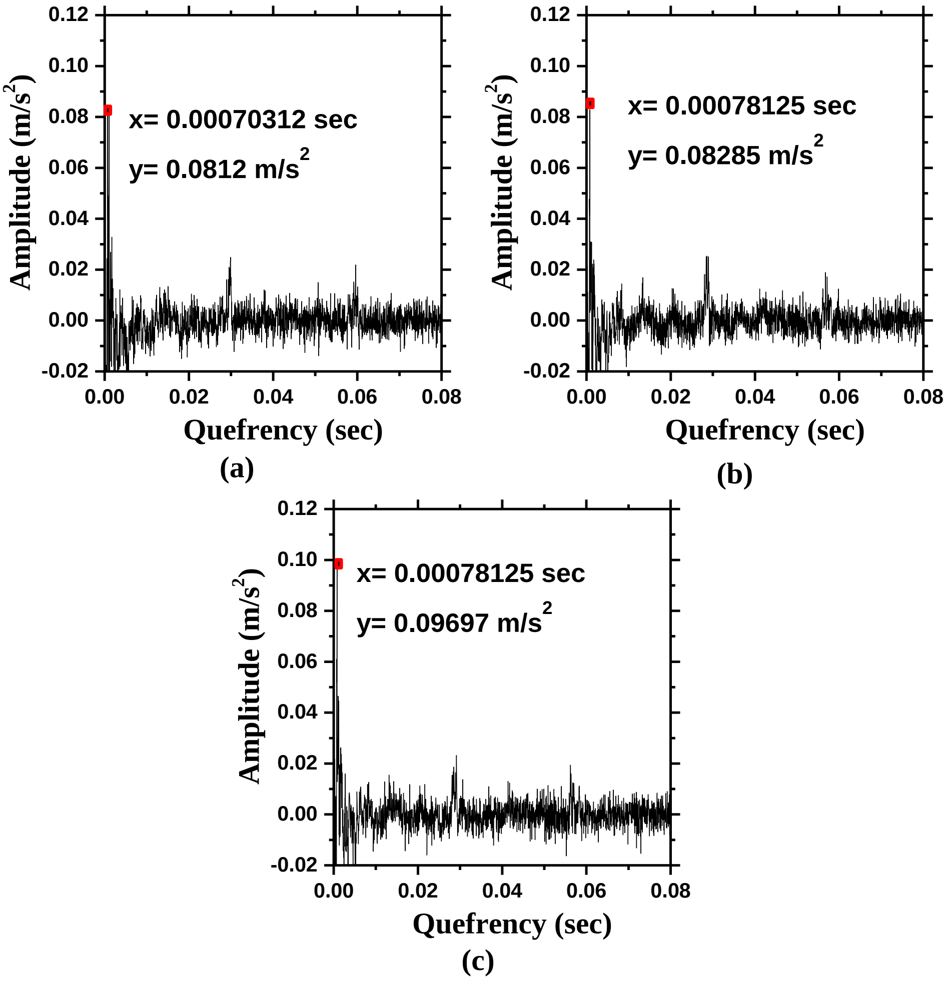


Figure 4.12 Cepstrum plots of load1 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

In Figure 4.13(a), (b) and (c) for healthy, 50% defect and 100% defect conditions, the quefrency is about 0.00078125 sec and corresponding accelerations are 0.0643 m/s^2, 0.0857 m/s^2 and 0.0973 m/s^2 respectively.

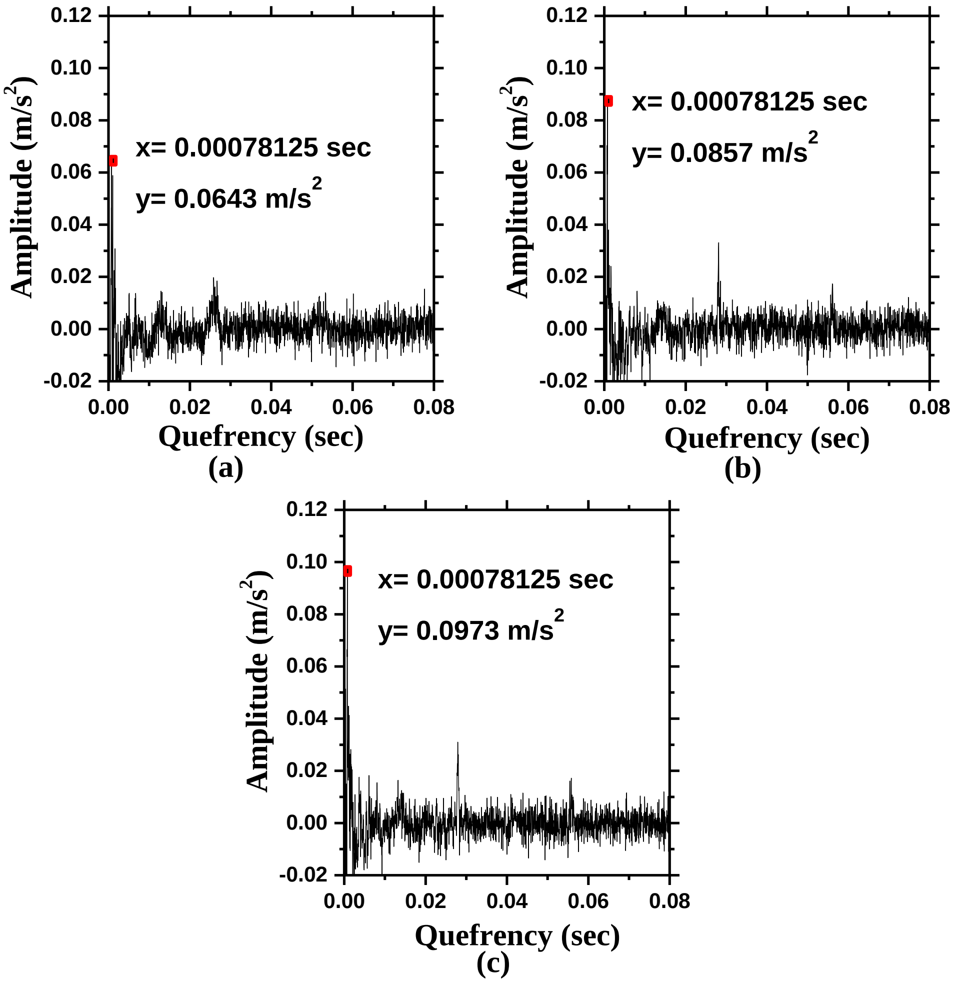


Figure 4.13 Cepstrum plots of load2 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

From the above discussion, it is clear that spectrum and cepstrum analysis of the gearbox provides information of frequency and quefrency but there is a drawback that no information of time period is available in the FFT and cepstrum plots. For further detailed understanding other time frequency methods need to be implemented. In next sub sections, STFT and wavelet transform methods have been discussed for analyzing the gearbox conditions.

4.4.4 Short time Fourier transform

FFT analysis is suitable only for analyzing stationary signals. Since engine gearbox vibration signals are non-stationary, analysis of vibration signals is performed using STFT. For understanding non-stationary nature of engine gearbox vibration signals, the windowing function with Fourier transform was used. Here, different window functions were compared and the better performing one was adopted in the analysis. Figure 4.14, 4.15 and 4.16 illustrate the STFT time-frequency plots for no load, load1 and load2 with different conditions of the gearbox respectively.

In Figure 4.14, frequency band of about 1000–1300 Hz was excited by gearbox fault. This band indicates 3rd or 4th harmonics of GMF which increased as the fault condition increased. Similarly, for load1 and load2 conditions, the excited band increased slightly in the band of 1000-1300 Hz when compared to no load condition.

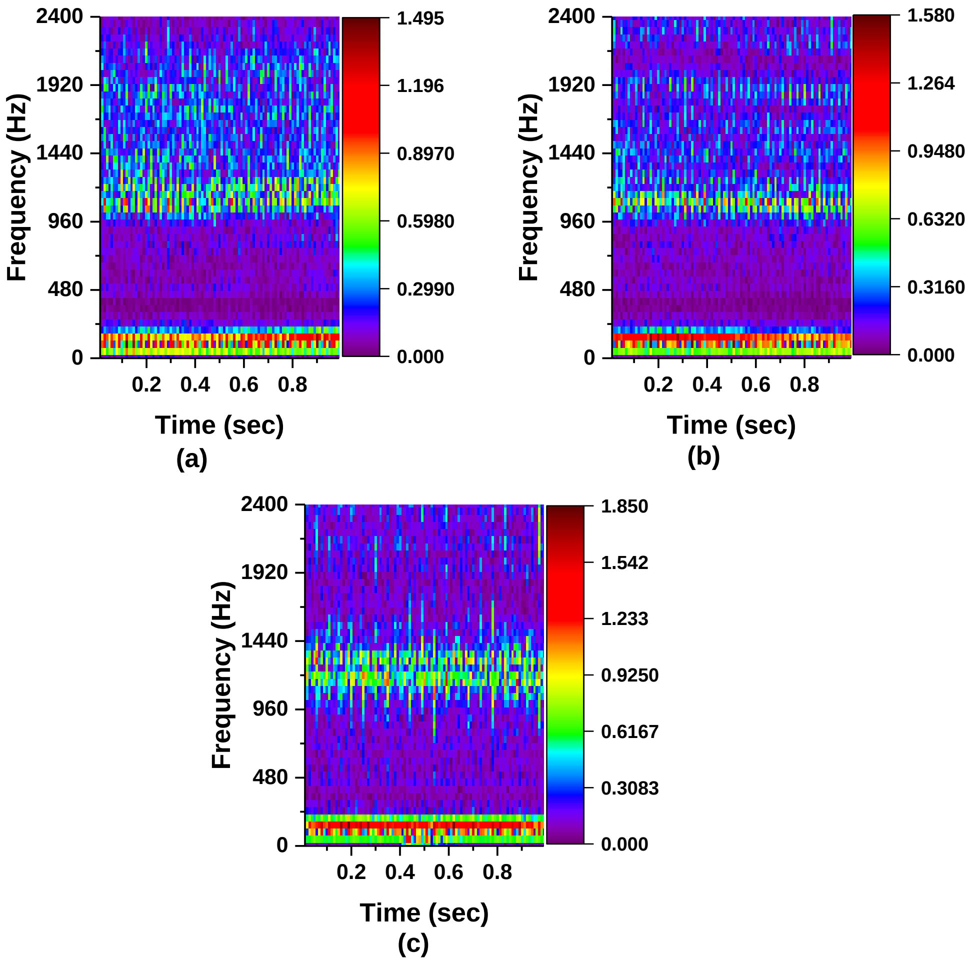


Figure 4.14 STFT plots of no-load condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

Figure 4.15 depicts time frequency plots for load1 condition and indicates increasing level in band of frequency in the range of 1000-1300 Hz. In these time-frequency plots, excited band is giving information about faults in the gearbox but the extent of amplitude variation is unclear under a particular fault condition.

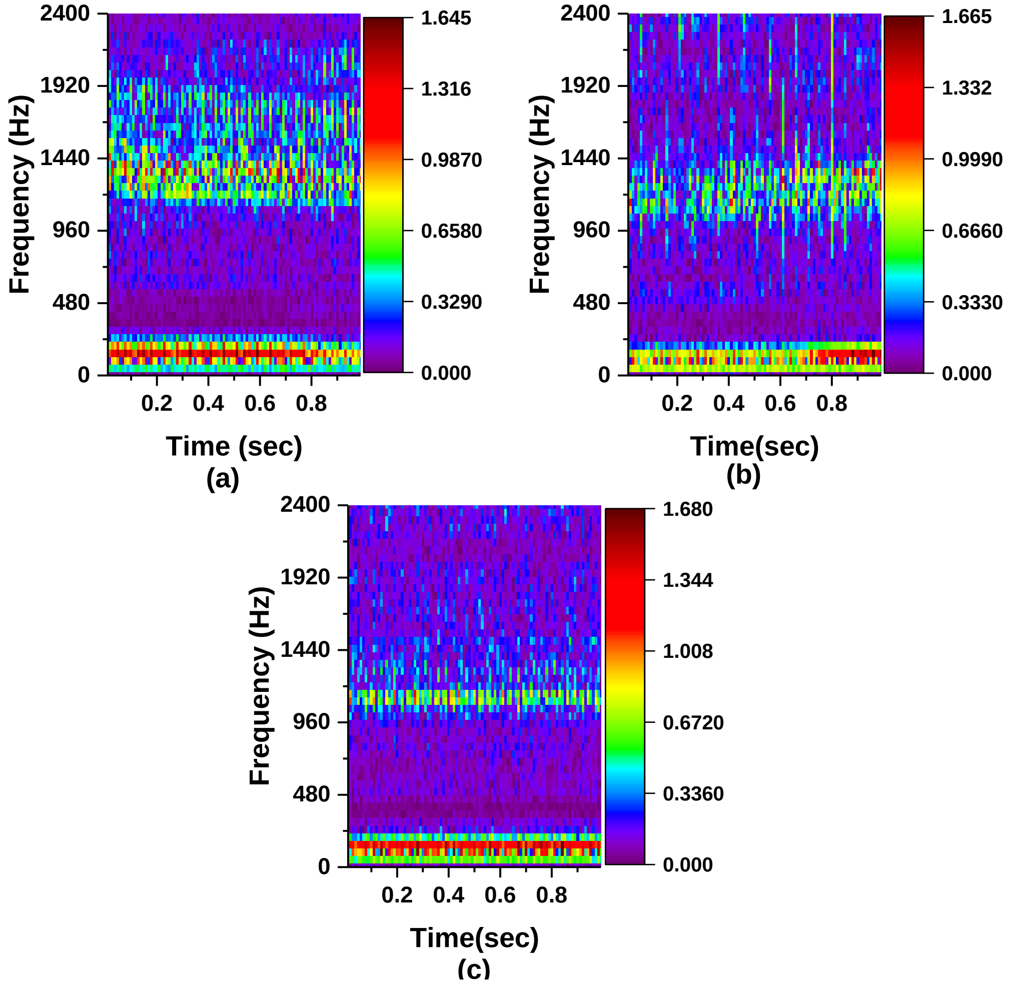


Figure 4.15 STFT plots of load1 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

Similarly, Figure 4.16 shows time frequency plots for load2 condition and these plots display increasing band of frequency in the range of 1000-1300 Hz. In STFT analysis, selecting, the window function is very tedious and to get information about time, frequency resolution will be lost and vice versa. To address this problem, wavelet analysis is adopted in the next subsection.

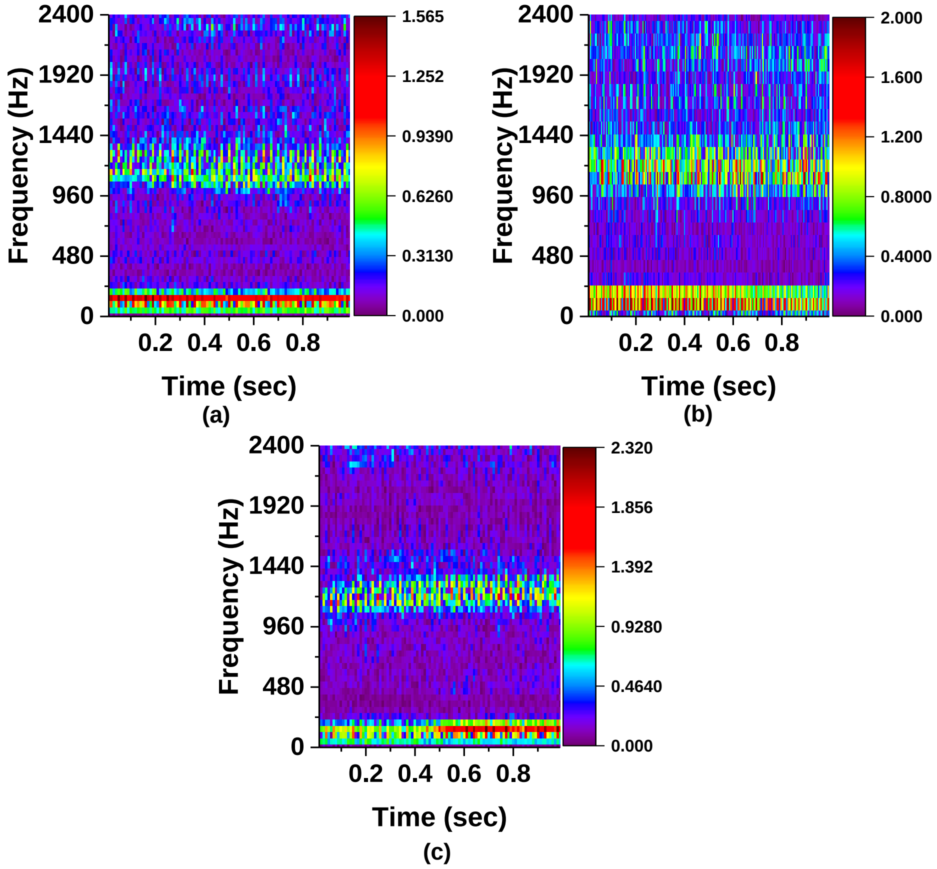


Figure 4.16 STFT plots of load2 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

4.4.5 Continuous wavelet transforms

Figure 4.17, 4.18 and 4.19 show the CWT plots of IC engine gearbox under different conditions such as healthy, 50% defect and 100% defect with varying load conditions respectively. CWT plots for no load, load1 and load2 describe the time-frequency information very clearly with variation of amplitude as the gear condition changes from healthy to 100% defect condition.

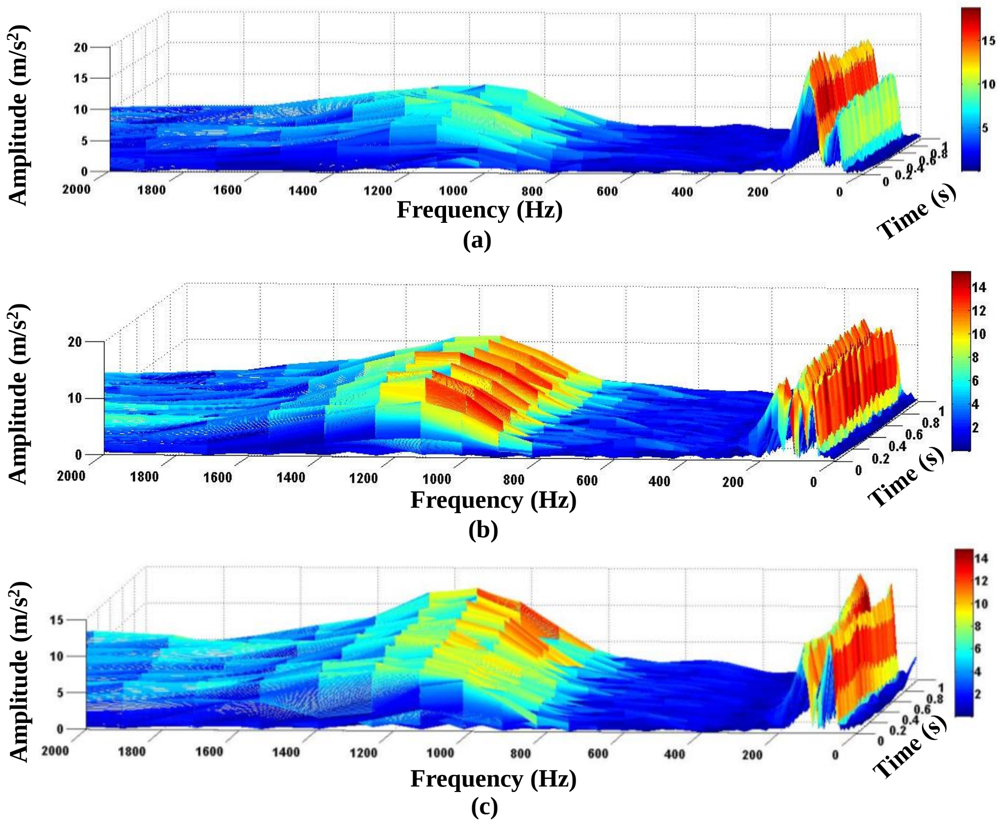


Figure 4.17 CWT plots of no-load condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

In Figure 4.17(a) at no load with healthy condition, frequencies are concentrated at 800-1500 Hz with acceleration level of 15 m/s^2. In Figure 4.17(b) for no load with 50% defect condition, frequencies are concentrated at 800-1500 Hz with acceleration level of 14 m/s^2. In Figure 4.17(c), for no load with 100% defect condition, frequencies are concentrated at 800-1500 Hz with acceleration level of 14 m/s^2. As the loading condition changes from load1 to load2, the increase in amplitude for different conditions of gearbox shows significant increase in the acceleration level up to 25 m/s^2. This increase in amplitude of gearbox indicates that faulty gear produces higher impacts on the gearbox casing if any abrupt change occurs during running of an engine.

In Figure 4.18(a) for load1 with healthy condition, the acceleration level is 14 m/s^2 and for load1 with 50% defect and 100% defect, acceleration levels increase up to 15 m/s^2 and 25 m/s^2 respectively. This vibration impacts can be clearly observed in Figure 4.18(c).

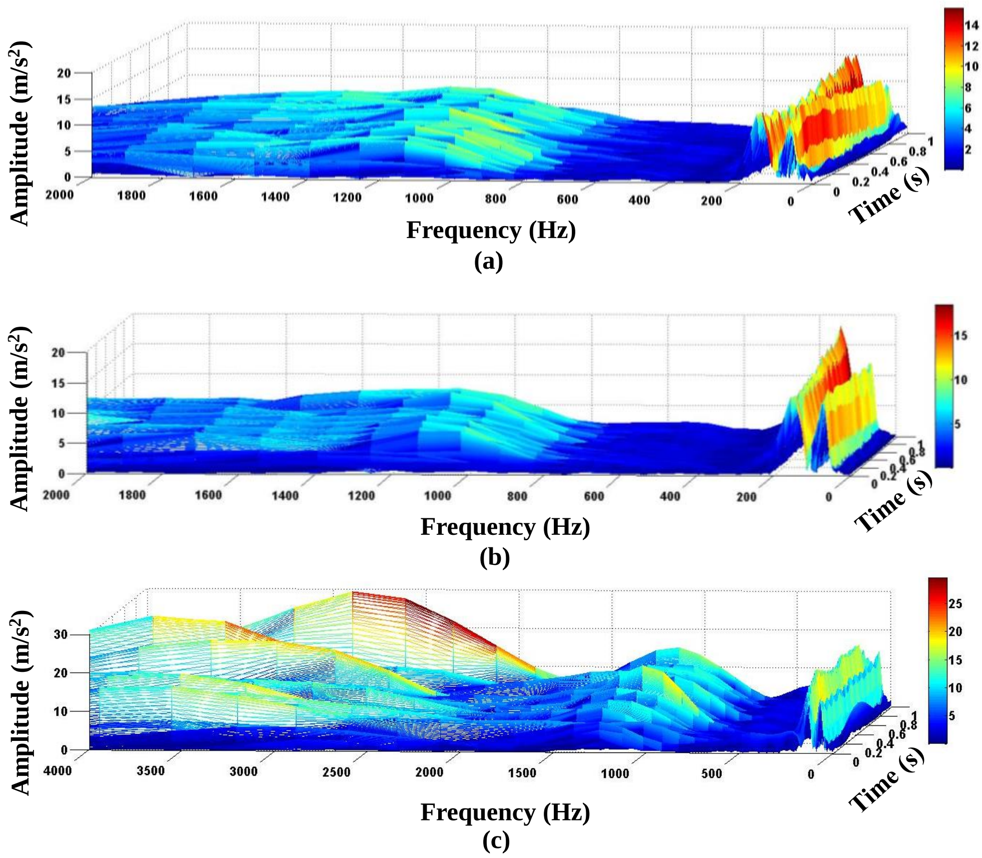


Figure 4.18 CWT plots of load1 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

Similar trend can be seen in load2 condition in Figure 4.19 (a), (b) and (c) for healthy, 50% defect and 100% defect conditions respectively. In Figure 4.19, the acceleration level for healthy condition is 15 m/s^2, for 50% defect is 15 m/s^2 and for 100% defect is 25 m/s^2 and also harmonics are clearly indicating the time at which these higher magnitudes of vibration occur due to gearbox defect conditions.

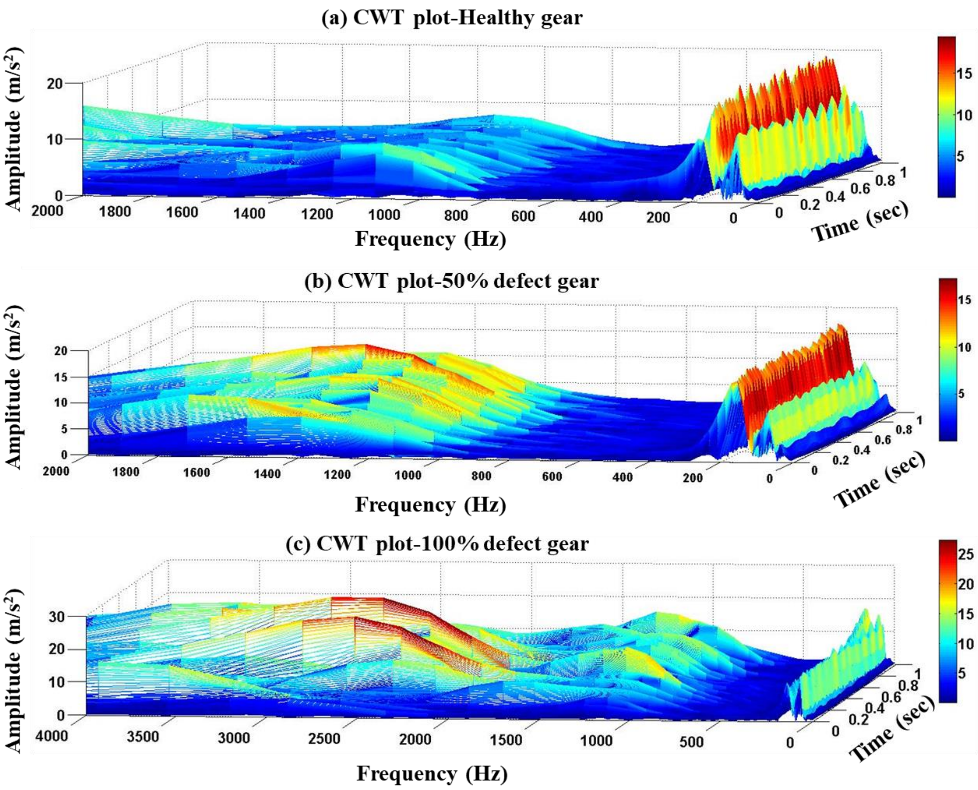


Figure 4.19 CWT plots of load2 condition (a) Healthy tooth, (b) 50% defect tooth, (c) 100% defect tooth

In comparison with different signal processing techniques, wavelet analysis provides better information for time-frequency analysis with variation of amplitude. Also, CWT plots clearly, indicate harmonics of frequency, as load increases with respect to gear faulty conditions in load1 and load2 conditions. To develop an automatic fault diagnosis system, ML techniques are essential and details of the ML techniques are discussed in next chapter.

4.5 SUMMARY

This chapter has illustrated the analysis of vibration signals acquired for healthy and different faulty conditions of gearbox elements such as bearing and gear using the time domain analysis, spectrum analysis, cepstrum analysis and wavelet transform analysis for detecting the faults. It was found that the time domain analysis gives overall vibration level but do not provide any fault diagnostic information. Spectrum analysis is the most widely used signal processing technique, but sometimes quite difficult to identify the defect frequency and it requires expertise in the domain.

Cepstrum analysis is a suitable method to identify and distinguish the fault quefrencies. Wavelet analysis is three-dimensional representation of a signal which is inherently suited to indicate transient events in the signals. Since IC engine gearbox generates non-stationary signals and complex signals, fault diagnosis of gearbox can be effectively monitored using advanced signal processing technique rather than traditional approaches. Machine learning approach is one of the promising tools which can be easily applied for fault diagnosis. Chapter 5 presents the techniques used for fault diagnosis of the gearbox of an IC engine using machine learning approach for online tool condition monitoring.

CHAPTER 5

FAULT DIAGNOSIS OF IC ENGINE GEARBOX USING MACHINE LEARNING TECHNIQUES

5.1 INTRODUCTION

Machine learning (ML) is a branch of artificial intelligence related to the development of techniques for computers to learn. More specifically, ML is an approach for building computer programs by analysing large data sets. Most of the ML methods are iterative in nature and require high-speed processors in order to function properly. Because of the advances in technology, the application of ML methods for solving problems in real time has become more popular. ML methods are widely used in a variety of applications, such as image processing, structured data analysis, market analysis, medical, automation and fault diagnosis. This chapter explains investigation of the vibration signals of a gearbox in an IC engine using ML methods, which are used to diagnose faults in the gearbox.

5.2 MACHINE LEARNING APPROACH

ML approach comprises of three phases, namely; (i) feature extraction, (ii) feature selection, (iii) feature classification. In feature extraction, the significant hidden information available in the acquired vibration signals are extracted in the form of statistical features, discrete wavelet features and empirical mode decomposition features. In the feature selection phase, a subset of the existing features is selected without any transformation. In the present study, decision tree algorithm is used as a feature selection technique. ML method has two steps in the third phase. Initially, classification algorithms are trained with the help of features selected from the *training data* of different fault signals. In the second step, the trained algorithm is evaluated using selected features from the *test data*. The classification phase identifies the class of fault. In the current research, classifiers such as support vector machine (SVM), random forest tree and K star algorithms are used.

The flow chart of ML method followed to diagnose gear faults and bearing faults in an IC engine is depicted in Figure 5.1.

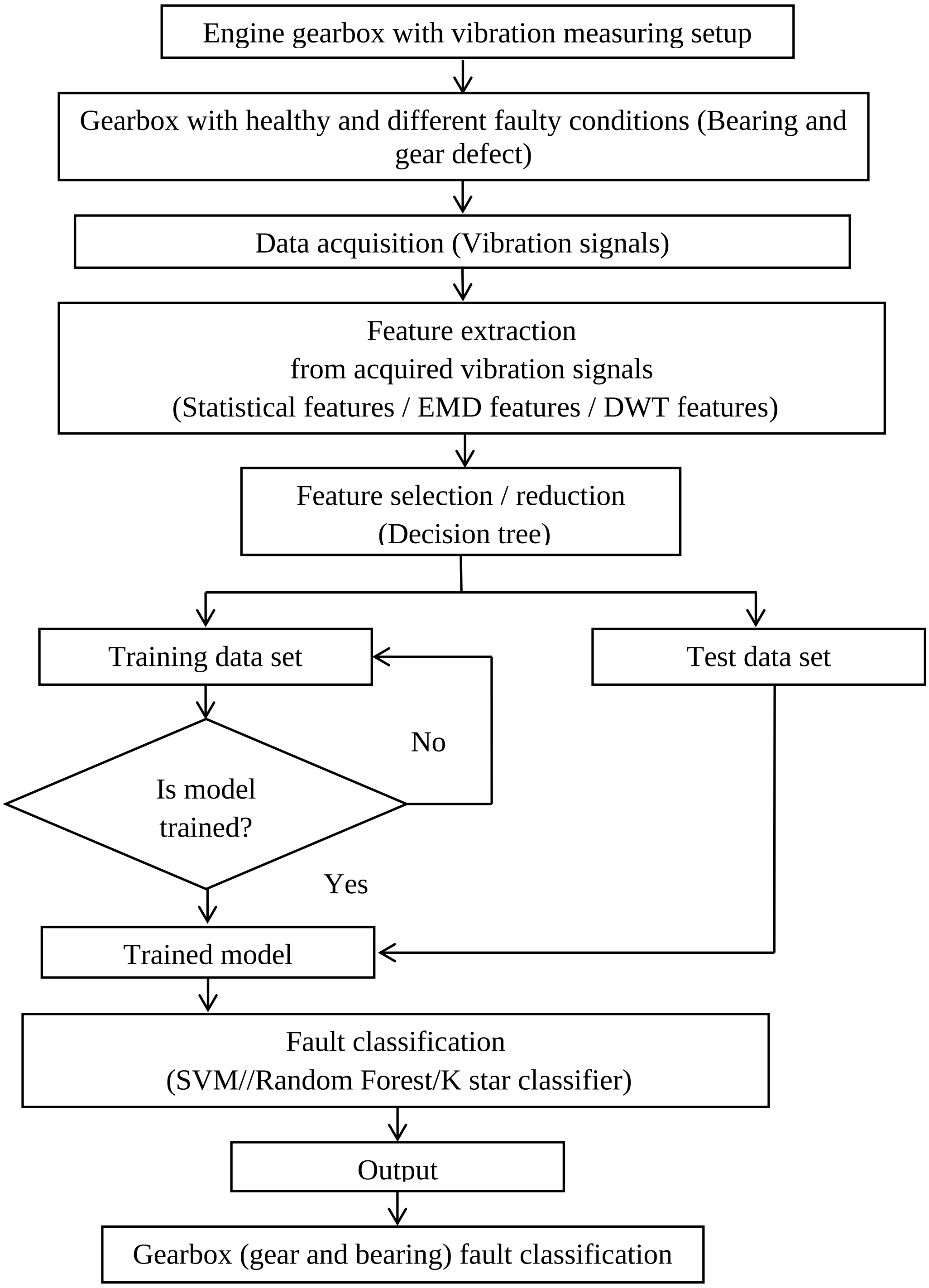


Figure 5.1 Flow chart of machine learning technique

A significant amount of work has been carried out in the past to determine the efficiency of ML methods for fault diagnosis. Many previous studies considered either one element or two elements with limited set of fault classes. It is important to verify the ability of ML methods in classifying multiple faults in multiple elements of mechanical system. Also, it is important to study the influence of number of faults on various elements in fault diagnosis. Identifying the number of faults is difficult because the sensor signal with one fault or many faults resemble similar. Hence identifying that significant feature that distinguishes between signals is critical. Only a few researchers have reported the application of ML techniques to analyse gearbox vibration signals in order to diagnose the faults. Hence, a detailed investigation is needed in this area. The current study discusses diagnosis of gearbox elements such as bearings and gears in a four-stroke internal combustion engine.

The following section explains the steps involved in machine learning techniques. ML has three important phases namely;

- Feature extraction- Statistical features, Discrete wavelet features, Empirical mode decomposition features
- Feature selection-(Decision tree- J48 algorithm)
- Feature classification- Bearing fault diagnosis, Gear fault diagnosis

5.2.1 Feature extraction

Feature extraction is the process which transforms or projects the original data set into a new subspace which has a smaller number of dimensions. This is also called dimensionality reduction. It gives useful information about the acquired signals. In this study, vibration signals undergo statistical, empirical mode decomposition and discrete wavelet transform feature extraction methods. The details of these methods are discussed in the following sections.

5.2.1.1 Statistical features

From the vibration signals, statistical features such as mean, mode, standard deviation, skewness, standard error, sample variance, maximum, minimum, range, median, sum and kurtosis were extracted under different conditions of the engine gearbox. These are described in brief as follows.

Maximum:- The maximum is the highest value in the given data set.

Minimum: - Minimum is the lowest value in the given data set.

Mode:- The mode is the number that frequently occurs in the set of data.

Range:- The range is the difference between the uppermost and lowermost value in the given information set.

Median: - Median is the mid-value in the sequence of numbers.

Sum:- The sum is referring to the summation of all the feature values in the given data set.

Mean: - Mean is the set of the average of all the data points and is given by equation (5.1).

$$Mean(\overline{x}) = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{5.1}$$

Standard deviation: - Standard deviation (SD) is the proportion of how spread-out numbers are in a given data set and is given by equation (5.2).

$$SD = \sqrt{\frac{\sum x^2 - (\sum x)^2}{n(n-1)}} \tag{5.2}$$

Skewness: - Skewness is the asymmetry from the mean of data distribution and is given by equation (5.3).

$$Skewness = \frac{n}{n-1}\sum\left(\frac{x_i - \overline{x}}{s}\right)^3 \tag{5.3}$$

Variance: - Sample variance is the square of the standard deviation and can be calculated by equation (5.4),

$$\sigma^2 = \frac{\sum x^2 - (\sum x)^2}{n(n-1)} \tag{5.4}$$

Standard error:- The standard error refers to the error coming across when a measurement of sampling distribution differs from its value and is given by equation (5.5).

$$SE = \frac{\sigma}{\sqrt{n}} \tag{5.5}$$

Kurtosis: - Kurtosis is the value used to define the variation of given data around the mean and is given by equation (5.6)

$$kurtosis = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{x_i-\bar{x}}{s}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{5.6}$$

where, x - is the sample

n - is the number of samples per second

$\bar{x}$- is the mean

σ- is the variance

s- is the standard deviation

5.2.1.2 Empirical mode decomposition

EMD is adaptive transform, time-space analysis method suitable for non-stationary and non-linear signals. EMD is a method of breaking a time series data into components called intrinsic mode functions (IMF). These modes provide insight into the signal. IMF have mean value zero and one extreme between zero crossings. EMD uses sifting process to decompose signal into IMF. For an initial sequence a mean n is computed m using the upper and lower envelope from a cubic spline interpolated between maxima and minima. Arbitrary parameter is used for locality.

The effectiveness of EMD depends on the arbitrary point selected. The steps followed to obtain the EMD is as follows

The first component is computed as

$$b_1 = X(t) - n_1 \tag{5.7}$$

The first IMF contains high frequency oscillations which are marked as noise in the initial sequence, are rejected. The procedure followed to extract IMF from its initial sequence is called sifting.

In the second sifting process b_1 is treated as data and n_{11} is the mean of b_1 with upper and lower envelopes.

$$b_{11} = b_1 - n_{11} \tag{5.8}$$

The sifting is repeated k times until b_{1k} is IMF i.e.,

$$b_{1k} = b_{1(k-1)} - n_{1k} \tag{5.9}$$

Then, b_{1k} is designated as

$c_1 = b_{1k}$, the first IMF from the data.

This first IMF contains high frequency noise, it is separated from rest of the data

$$X(t) - c_1 = r_1 \tag{5.10}$$

The procedure is repeated on r_j which results in set of intrinsic mode functions. The number of IMFs derived depends on length of signal (Max Lambert, Andrew Engroff, Matt Dyer 2020). Sifting stops when residue r_n becomes monotonic. The components derived from EMD are synthetic and helpful in understanding the structure of the input data and facilitates its analysis.

Energy amplitude E_{ni} of the IMF is calculated by equation (3.18)

$$E_{ni} = \sum_{i=1}^{m} |c_i(t)|^2 \tag{5.11}$$

Here m is discrete data length of concerned IMF function

A vector of energy function which can be used as features is constructed as shown in equation (5.12).

$$T = \{E_{n1}\ E_{n2}\ E_{n3} \dots \dots E_{nm}\} \tag{5.12}$$

Here n is number of IMF`s. Normalizing the feature vector (T) is done to avoid dominance of larger attributes over smaller numeric range, since some IMF generated might have larger IMF energy. $\acute{T}$ is normalized feature vector which is used as input to classifiers as given in equation (5.13) (Vernekar et al. 2017).

$$\acute{T} = \left\{\frac{E_{n1}}{E}, \frac{E_{n2}}{E}, \dots \dots, \frac{E_{nm}}{E}\right\} = \{E_1, E_2, \dots, E_n\} \tag{5.13}$$

5.2.1.3 Discrete wavelet transforms features

The Wavelet transform provides a better representation of the signal by considering different time-scales and also different coefficients of wavelet using a small wavelet basis function. This small wavelet basis function is a short wave with finite energy features. Many applications in the fields of engineering and mathematics, like signal denoising, compression, image processing and feature extraction techniques, use wavelet transform extensively for getting hidden information. DWT is one such type of wavelet transform technique with a fast algorithm based on conjugate quadratic filters. Mathematically, DWT is represented by the following equation (5.14).

The DWT of a signal x(t) is indicated by

$$dwt(j,k) = \frac{1}{\sqrt{2^j}} \int x(t)\psi^*\left(\frac{t-k2^j}{2^j}\right) dt \qquad (5.14)$$

Wavelet coefficients are computed using the following expressions (5.15) to (5.18).

$$\phi(t) = \sqrt{2}\sum_k h(k)\phi(2t-k) \qquad (5.15)$$

$$\psi(t) = \sqrt{2}\sum_k g(k)\phi\,(2t-k) \qquad (5.16)$$

$$a_{j,k} = \sum_m h(2k-m)a_{j-1,m} \qquad (5.17)$$

$$d_{j,k} = \sum_m g(2k-m)a_{j-1,m} \qquad (5.18)$$

Here, *h(k)* is a high pass filter and *g(k)* is a low pass filter. These filters are chosen based on the wavelet function $\psi(t)$ and scaling function $\phi(t)$. The low-frequency component $a_{j,k}$ is an approximation coefficient derived from the low-frequency filter and the high-frequency component $d_{j,k}$is a detail coefficient derived from the high-frequency filter. Figure 5.2 displays the approximation and detail coefficient of DWT.

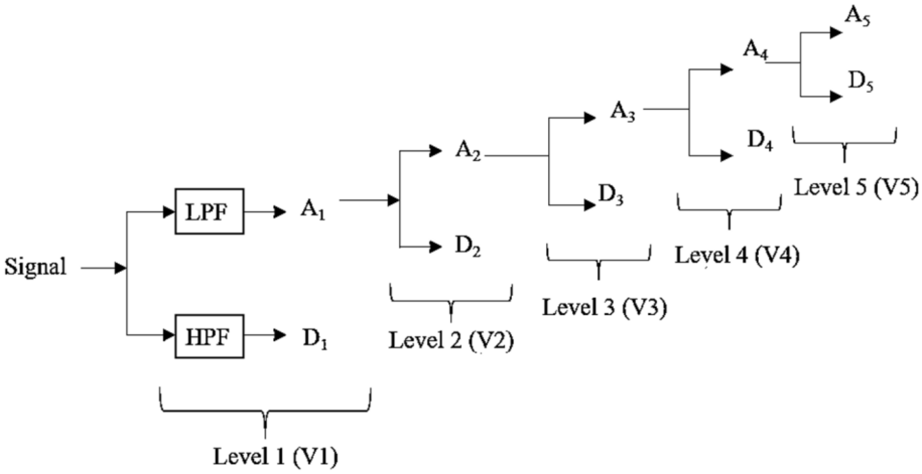


Figure 5.2 Approximations and detail coefficients of DWT

The details of the DWT feature with its feature vector can be found in studies(Aralikatti et al. 2020; Vernekar et al. 2015).

$$v_i^{dwt} = \{v_1^{dwt}, v_2^{dwt}, \ldots v_n^{dwt}\}^T \tag{5.19}$$

v_i^{dwt} is the element associated to the different resolutions and can be calculated as follows;

$$v_i^{dwt} = \frac{1}{ni} \sum_{\mathrm{j=1}}^{\mathrm{ni}} \mathrm{W}_{\mathrm{i,j}}^2 \;\; ; \;\; \mathrm{i} = 1,2, \ldots .8 \tag{5.20}$$

where $n_1=2^7$, $n_2=2^6$,….. $n_8=2^0$,

v_i^{dwt} is i^{th} DWT feature vector,

n_i is the number of samples in the sub band,

$w_{i,j}^2$ is the sub-band for the j^{th} detailed coefficient.

v_i provides mean square value of the decomposed signal at various levels

These extracted DWT(v1-v8) feature vectors with different classes are considered as input to the decision tree for choosing important features, to reduce computational time. The following section describes the details of the feature selection.

5.2.2 Feature selection

The feature selection process is different from feature extraction. Here, no new features are generated. Given a set of features F = $\{x_1 \ldots x_n\}$, feature selection is to find a subset of $F' \subseteq F$ that maximizes the learners ability to classify the patterns. In machine learning, feature selection is also known as variable selection, attribute selection, or variable subset selection. It is a process of selecting a subset of relevant features (variables, predictors) for use in model construction. The importance of feature selection methods is as follows.

- This is more important when the number of features are very large.
- Need not use every feature for creating an algorithm.
- It can assist the algorithm by feeding only those features that are really important.

The more contributing features will have feature value with minimum variation within a class and maximum variation between the classes. The role of feature selection methods in machine learning is given as follows.

- It enables the machine learning algorithm to train faster.
- It reduces the complexity of a model and makes it easier to interpret.
- It improves the accuracy of a model if the right subset is chosen.
- It reduces overfitting.

There are several feature selection techniques available in machine learning; among them, the decision tree technique is widely used for feature selection in the area of fault diagnosis of mechanical components.

5.2.2.1 Decision tree (DT) or J48 algorithm

In this investigation, the DT was used for the selection of features. DT is an approach used to order information into discrete structures utilizing tree shape algorithms. The fundamental motivation behind the DT is to depict the mechanical evidence included in the data. This method finds application in engineering, marketing, medical and statistical surveying measurements. A typical DT is characterized by the J48 decision tree algorithm in the WEKA C4.5 algorithm. It comprises of branches, number of leaves, number of nodes and one root node. The occurrence of feature components in a DT signifies the critical information from the related feature available in the selection method. An individual branch in a tree signifies a series of nodes from the root to the leaf and every node characterizes a feature or attribute. The method of construction of the DT and the use of the same for the selection of features are described below.

- The group of features is given as input to the WEKA C4.5 algorithm and resulting outcome yields a DT.
- In the DT branches, each analytical value of the originated feature node is displayed.
- It consists of a leaf node that specifies class names and whatever nodes remain associated with the classes are the ones that are actually classified in the tree.
- Beginning from the root node of the tree to the node of the leaf, essential vectors of the feature are classified with the use of DT.
- In every single tree, the decision node is the most valuable feature.

The valuable features distinguished in view of the standards which raise the ideas of entropy and information gain decrease are discussed in the following section.

- ***"Information gain" and "Entropy reduction"***

Information gain is an anticipated decrease in entropy by apportioning the samples given in the attribute. Entropy is the amount of impurity present in a group of instances. It will reduce uncertainty by adding information. This information gain associates the entropies of the original classification and the classification after information inclusion. This gain (S, A) of an attribute 'A' to a group of instances 'S' can be calculated using equation (5.21)

$$Gain(S, A) = Entropy(S) - \sum_{v \in Value(A)} \frac{|S_v|}{|S|} Entropy(S_v) \tag{5.21}$$

In the equation (5.21), 'A' has value 'v', 'S_v' is the subset of 'S' for the feature (A) and value (A) is the arrangement of all possible values for 'A' attribute.

The first part of the equation 'S' denotes the original group entropy and the second part is predictable entropy value of the set after 'S' is divided by the feature 'A' of the attribute. The predicted entropy portrayed continuously by the next part is immediate of the entropies of every subset. 'S_v' weighted by part of the tests $|S_v|/|S|$ that have a place with 'S_v' Gain (S, A) in this manner the normal decrease in entropy is caused by the significant estimation of a feature *'A'*. Entropy is given by equation (5.22).

$$Entropy(S) = \sum_{i-1}^{c} -P_i \log_2 P_i \tag{5.22}$$

In equation (5.22), *'c'* is the number of classes. *'P_i'* is the extent of *'S'* having a place with class *'$i.$'*

5.2.3 Feature classification

A classifier is an algorithm that is used to assign class labels to data points. Classifiers are more than just sorting unlabeled data into discrete classes. Classifiers have dynamic rules which can handle vogue and unknown values. Most classifiers use probability estimates to manipulate data classification. Each classifier is evaluated using a 10-fold cross-validation method. It is a method widely used for achieving high generalization accuracy.

The following steps are followed by a classifier:

- The dataset is divided into two parts: training data set and test data set
- Fit the classifier to the training data set (pre-processed dataset)
- Predict the test result
- Validate with 10-fold cross-validation

In the present study, classification is performed using following classifiers viz;

- Support vector machine
- K star
- Random Forest

The details of each classifier algorithm are described briefly in the following subsection.

5.2.3.1 Support vector machine

SVM is one of the classifiers which comes under supervised learning approaches used in machine learning systems in the field of regression and classification. It is an arrangement of interrelated controlled learning strategies that provide information and recognize designs. The SVM technique was first proposed by Vapnik and its cutting-edge manifestation was proposed by Coretes and Vapnik (Cortes and Vapnik 1995). The basic SVM manages the study of binary classification. Figure 5.3 shows the standard SVM classifier, where two different training data points (visually represented as squares and stars), are linearly classified. SVM performs the classification process by separating the training data set into two classes (namely positive classes as squares and negative classes as stars) in such a way that margin is maximized, so that generalization error is minimized. The nearest data points on which margin are defined is referred to as support vectors (Bansal et al. 2013). These points play an important role in the process of creating a hyper plane.

In the training data set, $\{(x_{i,}\ y_i)\}; i = 1\ to\ L, X_i \in\ R^n, y_i \in (1, -1)$ where *'x_i'* is the input vector and *'y_i'* is the indicator vector, *'L'* specifies total number of data points in the set. In the equation (5.23) and (5.24), *'w'* is the weight vector, *'ξ'* is the slack variable, *'b'* is the bias and $c > 0$ is the regularization constraint.

$$Minimize\ \ \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{L}\xi_i \qquad (5.23)$$

$$Subject\ to\ \begin{cases} y_i(w^T x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0; \qquad i = 1\ to\ L \end{cases} \qquad (5.24)$$

$$f(x) = sign\ (w^T x - \gamma) \qquad (5.25)$$

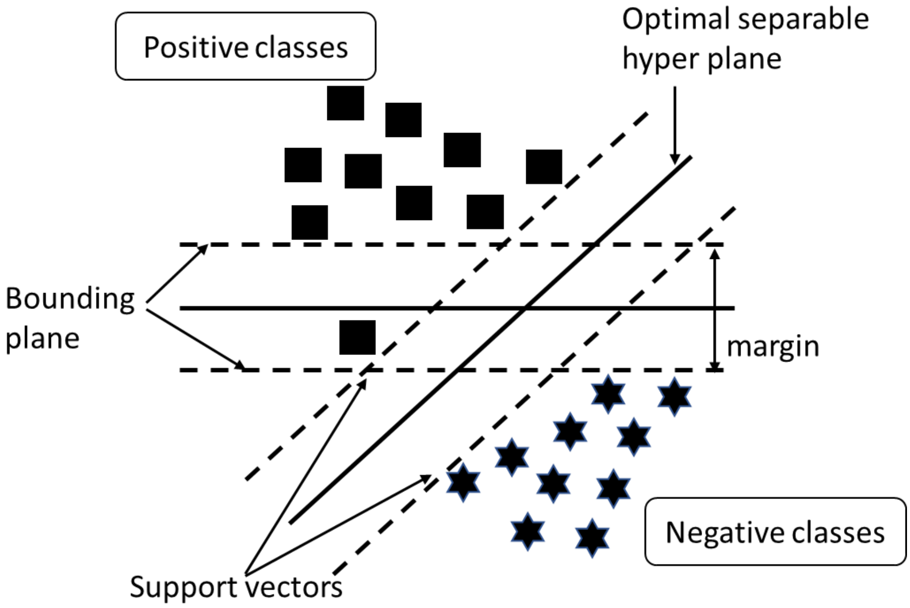


Figure 5.3 Classification of positive and negative classes using SVM

Where, *'w'* and *'γ'* are decision functions found from the equation (5.25). Decision functions will predict the new set of features of their class after completion of training. If *f(x)* value is positive, then a new set of features will be under a healthy class of bearing condition or else it will be in a faulty class of bearing condition. There are two types of SVM which have been developed, namely v-SVC and c-SVC which are used in the fault diagnosis of rotating machines (Bordoloi and Tiwari 2014b).

5.2.3.2 K star

K star is an instance-based classifier with entropy as a distance measure. It is consistent in handling real-valued attributes along with symbolic attributes. Summing transformations of all possible paths as a distance measure forms a unified approach for classification. The instance-based approach classifies an instance by comparing it with a pre-classified instance. A similar instance being classified is assumed to have a similar classification. The domain-specific distance function delivers quantitative similarity between instances to yield a final classification, then the instance is moved to a classification database. The algorithm used for category prediction and classification is detailed in this section.

Consider a set of instances I, such that transformations performed on set I yields T. Every instance in T maps to one another. Distinguished member σ belonging to T maps instances to themselves. Let P be set of prefix codes terminated by σ to form T*. Members of T* define a transformation on I:

$$\bar{t}(a) = t_n\big(t_{n-1}(\ldots.t_1(a)\ldots)\big)\; where\; \bar{t} = t_1, \ldots t_n \tag{5.26}$$

A probability function p is defined on T* which satisfies the following properties:

$$0 \leq \frac{p(\bar{t}u)}{p(\bar{t})} \leq 1 \tag{5.27}$$

$$\sum_u p(tu) = p(t) \tag{5.28}$$

$$p(\Lambda) = 1 \tag{5.29}$$

Hence,

$$\sum_{\bar{t}\in P} p(\bar{t}) = 1 \tag{5.30}$$

A probability function $P*$ is defined between say, instance a to b for all paths between the limits:

$$P^*(b|a) = \sum_{\bar{t}\in P:\bar{t}(a)=b} p(t) \tag{5.31}$$

K* function is defined as

$$K^*(b|a) = -log_2 P^*(b|a) \tag{5.32}$$

Here K* is obtained in terms of units of complexity by applying logarithm on P*. K* is non-zero and non-symmetric function.

The probability of an instance '*a*' belonging to category '*C*' is calculated by adding the probabilities of all the instances belonging to '*C*'.

$$P^*(C|a) = \sum_{b\in C} P^*(b|a) \tag{5.33}$$

The probability of classifying an instance for each category is calculated. The relative probabilities give an estimation of category distribution with instance space represented by a. The category with the highest probability of classification of the new instance is chosen for classification or by obtaining a normalized probability distribution for classification.

5.2.3.3 Random forest

Random forest (RF) is an ensemble supervised learning method. It can be used for both classification and regression (Liaw and Wiener 2002). Since it is an ensemble learning method, it takes the average of the predictions of each decision tree to achieve the final prediction output. In random forest, variables are given more importance due to their interaction with other variables. The variable's importance is estimated by observing prediction errors increase with out-of-bag (OOB) data for that variable while all other variables are left unaltered. RF is classified by two methods, namely, variable importance method and by proximity measure. In the variable importance method, the classification is done based on the interaction between instances by obtaining predicted error in relation to OOB computed. Classification using proximity measure is done by computing fractions of trees that fall into same node of similar observation using a proximity matrix. The variable importance method can also be used for model reduction.

The algorithm steps:

1. Draw n_{tree} bootstrap samples from the original data
2. Grow an unpruned classification for each bootstrap sample by randomly sampling m_{try} of predictors at each node and choose the best split among those variables
3. Predict new data by aggregating the predictions

Obtain error rate based on training data:

1. Predict the data at each bootstrap iteration (calling them out-of-bag)
2. Aggregate the OOB predictions and calculate the error rate

The necessary calculations are carried out tree by tree to form the forest. A lot of trees are required for stable estimates of variable importance. For classification problems with unbalanced class frequency, it is necessary to change the prediction rules(Breiman 2001; Pal 2005).

RF is a type of classifier consisting of an arrangement of trees sorted out into classifiers $\{h(x, \mathbf{\Phi}_k), k = 1, \ldots\}$ where $\{ \mathbf{\Phi}_k \}$ are free, indistinguishably dispersed random vectors and in each tree settles on a unit decision for the most prominent class for considering input x. RF combines the classifiers $h1(x)$, $h2(x), \ldots hk(x)$*and* gives a training set which is drawn extensively from the distribution of the random vectors X, Y. The margin function is given by

$$mg(X,Y) = av_k I(h_k(X) = Y) - max_{j \neq Y}\, a\, v_k I(h_k(X) = j) \qquad (5.34)$$

The margin estimates the degree to which number of votes at X, Y for the correct class surpasses the normal vote in favor of some other class. In equation (5.34), 'I' is the indicator function. A higher value of the margin indicates more trust in the grouping. The simplification error is given by equation (5.35).

$$PE^{*} = P_{X,Y}(mg(X,Y) < 0) \qquad (5.35)$$

The following section provides a detailed analysis and discussion on fault diagnosis of the IC engine gearbox using ML techniques.

5.3 FAULT DIAGNOSIS OF BEARING IN FOUR STROKE IC ENGINE

ML techniques are used to analyse the acquired acceleration signals and diagnose the bearing conditions. The current study focuses on feature extraction via statistical, EMD and DWT techniques. Following that, features are selected using the decision tree method and classification is performed using artificial intelligence techniques such as SVM, RF algorithms and K star models. Each step is explained through the experimental results, which are discussed in detail in the following subsections.

5.3.1 Fault diagnosis using statistical features

The information obtained from the acquired time domain data are called time-domain features. Descriptive statistical tool employed for computing time domain features. Statistical features such as mean, mode, standard deviation, skewness, minimum, maximum, range, standard error, variance, kurtosis and sum were extracted under healthy and faulty conditions of the bearing. Features tabulated in Table 5.1 are extracted from the time domain vibration signal, only 2 sample of each condition chosen for depiction. Features are used as inputs to classifier after selecting significant ones.

Table 5.1 Statistical feature extracted from bearing vibration signals

Sample number	**Mean**	**Standard error**	**Median**	**Mode**	**Standard deviation**	**Sample variance**	**Kurtosis**	**Skewness**	**Range**	**Minimum**	**Maximum**	**Sum**	**CLASS**
1	0.0008	0.0046	-0.0100	-0.754	0.736	0.542	3.080	0.049	10.53	-4.99	5.53	21.71	**Healthy**
2	0.0005	0.0047	-0.0021	-0.118	0.749	0.561	2.568	0.011	10.25	-5.08	5.17	13.30	**Healthy**
1	0.0103	0.0057	0.0052	-0.325	0.918	0.843	4.286	0.079	13.64	-6.40	7.24	264.12	**IR fault**
2	0.0093	0.0059	0.0111	-0.045	0.944	0.892	3.853	0.099	15.67	-7.28	8.39	239.02	**IR fault**
1	0.0077	0.0072	0.0130	-1.060	1.146	1.312	3.921	0.021	18.77	-9.96	8.80	196.57	**OR fault**
2	0.0072	0.0074	0.0092	0.236	1.179	1.389	5.104	0.109	22.23	-10.74	11.48	183.69	**OR fault**
1	0.0065	0.0067	0.0027	-0.075	1.076	1.158	30.699	-0.541	25.61	-13.17	12.44	167.68	**IR & OR Fault**
2	0.0059	0.0068	0.0025	0.240	1.083	1.174	31.164	-0.505	25.76	-13.20	12.56	151.49	**IR & OR Fault**

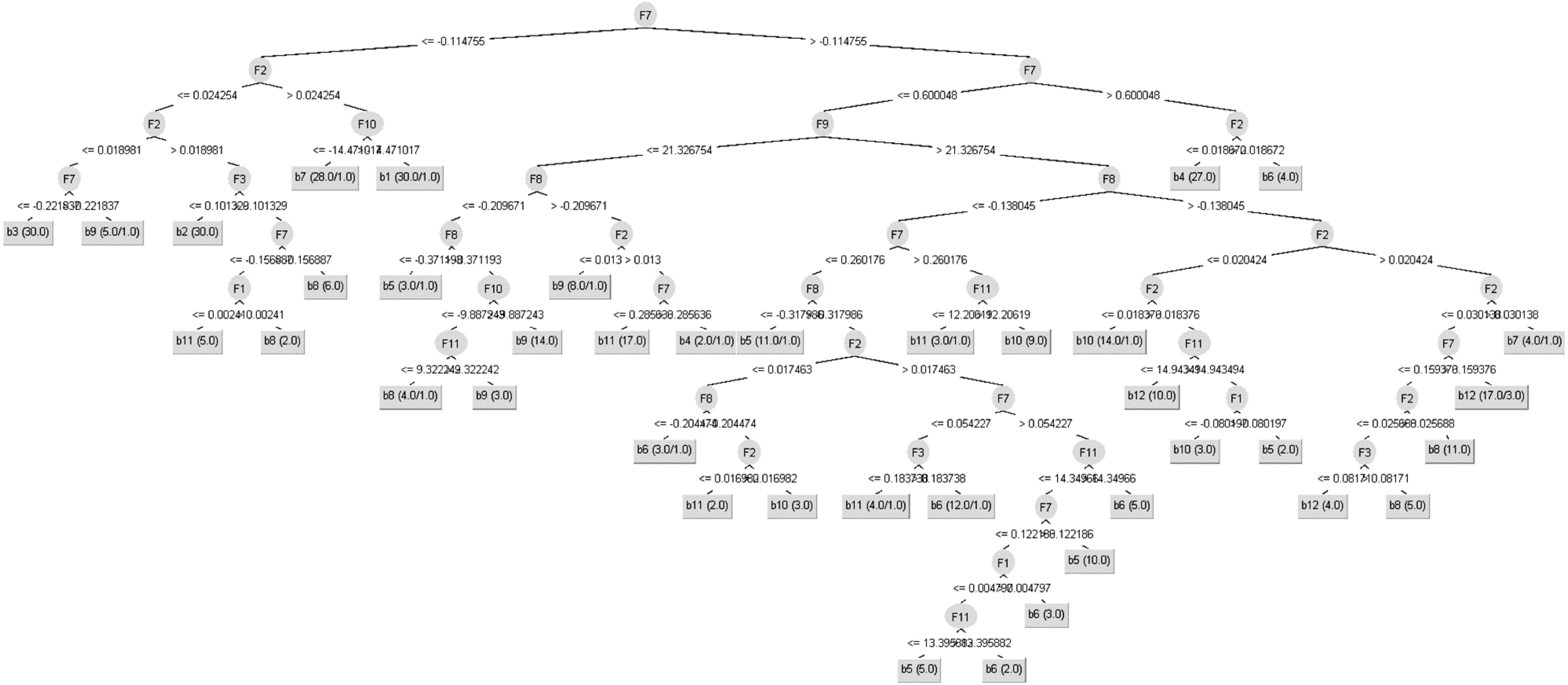


Figure 5.4 Decision tree of statistical feature of bearing data set in four stroke IC engine gearbox

5.3.1.1 Feature selection using decision tree

All extracted descriptive statistical features are used as an input to the decision tree and J48 algorithm constructs the decision tree with only significant features from set of extracted features. A data set of 360-samples are fed as input to the feature selection algorithm and corresponding output decision tree is shown in Figure 5.4. Classes are denoted by rectangular blocks (condition of the bearing) in obtained decision tree. Inside the parenthesis, two numbers are separated by a slash in rectangular blocks. The first number (in case of two numbers) or single number represents the number of data points (samples) that support in decision-making. The abbreviation used in decision tree are: **b1**=Healthy bearing with no load, **b2**=Healthy bearing with T1 torque, **b3**=Healthy bearing with T2 torque, **b4**=Spall at inner race with no load, **b5**= Spall at inner race with T1 torque, **b6**= Spall at inner race with T2 torque, **b7**= Spall at outer race with no load, **b8**=Spall at outer race with T1 torque, **b9**= Spall at outer race with T2 torque, **b10**=Spall on both inner race and outer race with no load, **b11**= Spall on both inner race and outer race with T1 torque, **b12**= Spall on both inner race and outer race with T2 torque. The features are indicated by F1-mean, F2-standard error, F3-median, F4-mode, F5-standard deviation, F6-sample variance, F7-kurtosis, F8-skewness, F9-range, F10-minimum, F11-maximum, F12-sum.

As observed from Figure 5.4, the tree structure of different classes has been formed in such a way that when F2 is greater than 0.024254 and F10 greater than -14.471017 value it is classified as healthy condition, whereas, when the F7 is greater than 0.024254 and F10 less than/equal to -14.471017 value it is classified as spall at outer race with no load condition and so on. The bearing conditions (healthy, spall at IR, spall at OR, Spall at both inner race and outer race) are represented as leaves in the tree. Among 12 features, except F4, F5, F6and F12 all other 8 features are selected by decision tree as most significant features. These selected features are treated as input to the classifiers such as SVM, random forestand K-star algorithms.

5.3.1.2 Feature classification

The objective of this investigation is to classify bearing conditions as healthy or faulty by using K star, RFand SVM. These classifiers are used most commonly in fault diagnosis of mechanical components. Ten-fold cross validation method is used for dividing data into training and testing the diagnosis model. This method divides data into ‘k’ equal parts every time and one set are used as testing samples and remaining ‘k-1’ is used as training samples. This is repeated for 10 times and average classification accuracy is obtained for the model. Classifier results are presented for bearing diagnosis in following subsection.

- ***K star algorithm***

The selected statistical features of vibration signals are given as input to the K star algorithm. The identified classification of the bearing conditions is presented in the Table 5.2.

Table 5.2 Confusion matrix of K star algorithm for bearing data set

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**class**
28	0	0	0	0	0	1	1	0	0	0	0	**a= b1**
0	30	0	0	0	0	0	0	0	0	0	0	**b=b2**
0	0	30	0	0	0	0	0	0	0	0	0	**c=b3**
0	0	0	24	1	0	0	0	1	3	1	0	**d=b4**
0	0	0	0	18	10	0	1	0	1	0	0	**e=b5**
0	0	0	0	10	13	0	0	3	0	1	3	**f=b6**
2	0	0	0	0	0	28	0	0	0	0	0	**g=b7**
1	0	0	0	2	0	0	20	4	0	2	1	**h=b8**
0	0	0	0	0	2	0	1	26	0	1	0	**i=b9**
0	0	0	1	2	3	0	0	0	20	2	2	**j=b10**
0	0	0	0	0	2	0	4	2	1	20	1	**k=b11**
0	0	0	0	0	2	0	3	0	0	0	25	**l=b12**

Table 5.2 illustrates the confusion matrix with K star algorithm as the classifier. Here, seventy-eight instances were misclassified and K star algorithm provided the classification accuracy of about 78.33% for the given vibration signals.

- ***RF algorithm***

Eight statistical features of vibration signals are given as input to the random forest algorithm. The identified classification of the bearing conditions is presented in Table 5.3.

It shows the confusion matrix with random forest algorithm as the classifier. Here, sixty-four instances were misclassified and random forest algorithm provided the classification accuracy of about 82.22% for the given vibration signals.

Table 5.3 Confusion matrix of random forest algorithm for bearing data set

a	b	c	d	e	f	g	h	i	j	k	l	class
29	0	0	0	0	0	1	0	0	0	0	0	**a= b1**
0	30	0	0	0	0	0	0	0	0	0	0	**b=b2**
0	0	30	0	0	0	0	0	0	0	0	0	**c=b3**
0	0	0	27	0	0	0	0	1	1	1	0	**d=b4**
0	0	0	0	18	7	0	0	3	1	0	1	**e=b5**
0	0	0	0	10	15	0	0	2	0	1	2	**f=b6**
2	0	0	0	0	0	28	0	0	0	0	0	**g=b7**
0	0	0	0	2	0	0	21	3	0	3	1	**h=b8**
0	0	0	1	1	0	0	2	24	0	2	0	**i=b9**
1	0	0	1	0	0	0	0	0	25	1	2	**j=b10**
0	0	0	1	0	3	0	2	0	0	23	1	**k=b11**
0	1	0	0	0	2	0	1	0	0	0	26	**l=b12**

▪ ***SVM algorithm***

The confusion matrix of the SVM model for statistical features of vibration signals are presented in Table 5.4. Based on the confusion matrix, 141 instances out of 360 instances were misclassified with classification accuracy of 60.83%. As the classification efficiency is considerably less as compared to random forest and K star algorithms, SVM with statistical features is not suitable for bearing fault diagnosis.

Table 5.4 Confusion matrix of SVM algorithm for bearing data set

a	b	c	d	e	f	g	h	i	j	k	l	class
30	0	0	0	0	0	0	0	0	0	0	0	**a= b1**
0	30	0	0	0	0	0	0	0	0	0	0	**b=b2**
0	0	30	0	0	0	0	0	0	0	0	0	**c=b3**
0	0	0	26	2	0	0	0	1	0	1	0	**d=b4**
0	0	0	0	25	0	0	0	1	4	0	0	**e=b5**
0	0	0	1	22	0	1	0	0	4	0	2	**f=b6**
11	0	0	0	0	0	19	0	0	0	0	0	**g=b7**
7	0	0	0	10	0	0	1	3	0	0	9	**h=b8**
0	0	0	0	4	0	0	0	26	0	0	0	**i=b9**
1	0	0	1	7	2	0	0	0	17	1	1	**j=b10**
1	0	0	1	9	0	0	1	17	0	0	1	**k=b11**
1	0	0	0	2	8	1	1	0	0	2	15	**l=b12**

▪ ***Summary***

The statistical features from the acquired vibration signals were extracted and the contributing features for classification were selected using decision tree (J48 algorithm) technique. The effectiveness of a selected set of features in identification of fault was presented. Table 5.5 summarizes the classification efficiencies of various classifiers with statistical features. The random forest algorithm has provided a highest classification efficiency of about 82.22% with statistical features as compared to the performances of other classifiers as shown in Table 5.5.

Table 5.5 Classification accuracy achieved with statistical feature for different classifiers for bearing data set

Classifier	**SVM**	**Random forest**	**K star**
Classification accuracy (%)	60.83	**82.22**	78.33

5.3.2 Fault diagnosis using EMD features

EMD decomposes the acquired vibration signals into IMFs as features for each class of the bearing condition. The first 8 IMFs contains mainly the dominant fault information, which is used to construct the amplitude energy feature vector to verify the performance of the proposed model. Feature energy vector T' were attained using equation 5.13 and served as an input vector to decision tree (J48 algorithm). Table 5.6 presents evaluated energy feature vector (two samples per each class) using EMD method.

Table 5.6 EMD feature extracted from bearing vibration signals

Sample No.	Class	E1	E2	E3	E4	E5	E6	E7	E8
1	**Healthy**	0.252	0.355	0.305	0.295	0.102	0.051	0.55	0.55
1	**Healthy**	0.400	0.573	0.486	0.361	0.148	0.083	0.238	0.238
2	**IR fault**	0.420	0.61	0.341	0.452	0.164	0.058	0.223	0.223
2	**IR fault**	0.526	0.606	0.277	0.447	0.231	0.118	0.074	0.074
3	**OR fault**	0.548	0.68	0.262	0.383	0.086	0.054	0.073	0.073
3	**OR fault**	0.599	0.715	0.249	0.221	0.096	0.044	0.057	0.057
4	**IR & OR Fault**	0.846	0.498	0.150	0.091	0.043	0.021	0.027	0.027
4	**IR & OR Fault**	0.554	0.765	0.258	0.176	0.077	0.033	0.032	0.032

5.3.2.1 Feature selection by decision tree algorithm

Each EMD feature represents a signal characteristic while, some features provide more information than others. Thus, all EMD features are fed into the decision tree (J48 algorithm) for feature selection. The decision tree for EMD features of vibration signals is shown in Figure 5.5. It has formed a tree like structure such that when E6 is greater than 0.0945, E2 is less than/equal to 0.62, then it classified as healthy bearing with T2 condition. Also, if E6 lies in between 0.0945 and 0.0462, then it is classified as healthy bearing with no load condition and so on.

The decision tree for EMD features is depicted in Figure 5.5 and it recognised E1, E2, E3, E4, E5, E6 and E7 as significant features. The classification will be carried out using these selected features.

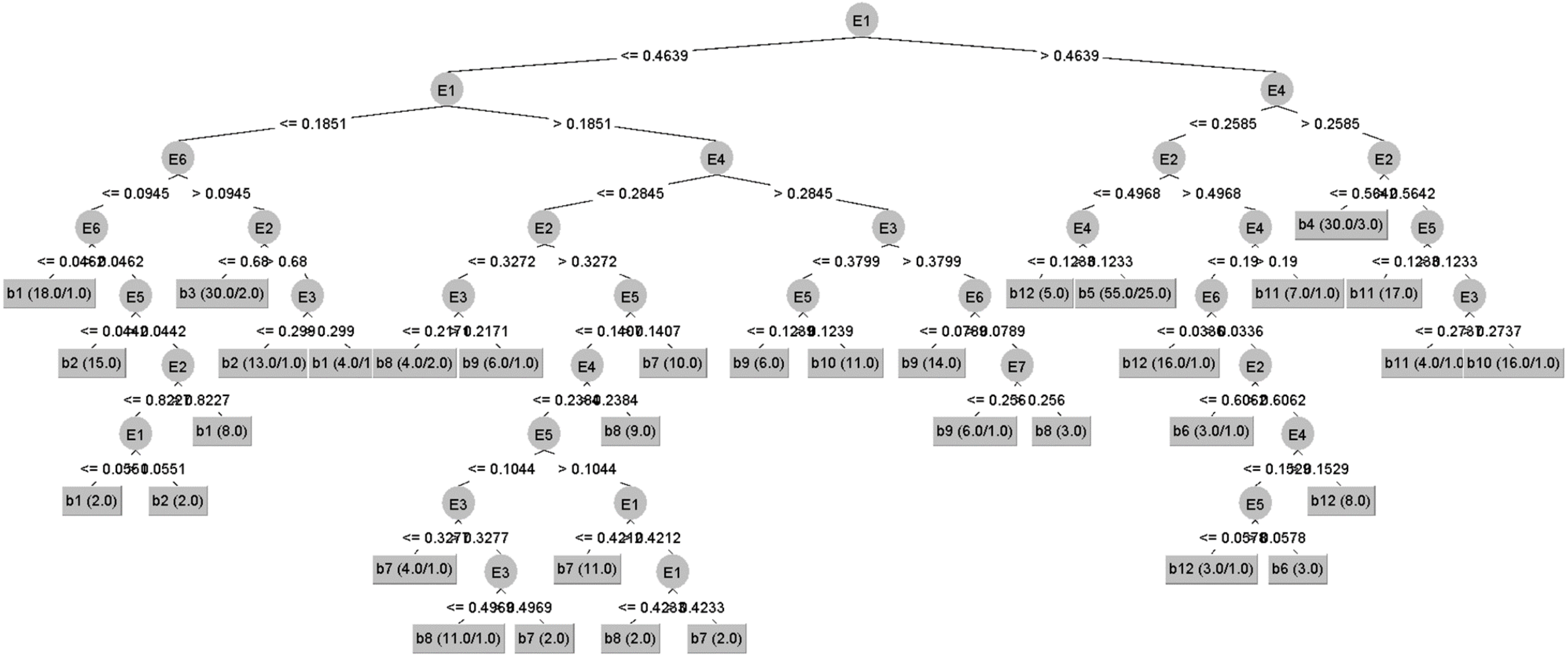


Figure 5.5 Decision tree of EMD feature of bearing data set in four stroke IC engine gearbox

5.3.2.2 Feature classification

The EMD features of vibration signals are analysed using classifiers namely SVM, random forest and K star models. The classifiers use significant features such as E1, E2, E3, E4, E5, E6 and E7 from all bearing conditions. The classifier test mode is 10-fold cross validated with training and testing data. The following table summarizes the results of each classification model in the form of a confusion matrix.

- ***RF algorithm***

The confusion matrix for ball bearing vibration signals is shown in Table 5.7. A data set of 360 samples contains 30 samples of each class of the bearing. From Table 5.7, out of 360 instances, 85 instances were misclassified by random forest algorithm with classification accuracy about 76.38% for the given vibration signals.

Table 5.7 Confusion matrix of random forest algorithm for EMD features of bearing

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**class**
26	3	1	0	0	0	0	0	0	0	0	0	**a= b1**
3	26	1	0	0	0	0	0	0	0	0	0	**b=b2**
0	2	28	0	0	0	0	0	0	0	0	0	**c=b3**
0	0	0	27	1	1	1	0	0	0	0	0	**d=b4**
0	0	0	0	17	13	0	0	0	0	0	0	**e=b5**
0	0	0	2	8	16	0	0	0	0	0	4	**f=b6**
1	0	0	0	0	0	24	5	0	0	0	0	**g=b7**
0	0	0	1	0	0	10	12	7	0	0	0	**h=b8**
0	0	0	0	0	0	0	3	25	2	0	0	**i=b9**
0	0	1	1	0	0	0	1	1	25	1	0	**j=b10**
0	0	0	0	0	1	0	0	1	2	23	3	**k=b11**
0	0	0	0	1	1	0	0	0	0	2	26	**l=b12**

- ***SVM algorithm***

The seven selected EMD features of vibration signals are given as an input to the SVM model. The outcome of the classifier is confusion matrix shown in Table 5.8. From the confusion matrix of SVM classifier with EMD features, it is found that 98 instances were misclassified and the classification efficiency is about 72.77%. SVM has a moderate classification accuracy for fault diagnosis, but is less efficient than the random forest algorithm. As a result, SVM models with EMD features are not recommended.

Table 5.8 Confusion matrix of SVM algorithm for EMD features of bearing

a	b	c	d	e	f	g	h	i	j	k	l	class
24	4	2	0	0	0	0	0	0	0	0	0	**a= b1**
3	26	1	0	0	0	0	0	0	0	0	0	**b=b2**
2	1	27	0	0	0	0	0	0	0	0	0	**c=b3**
0	0	0	29	1	0	0	0	0	0	0	0	**d=b4**
0	0	0	0	14	16	0	0	0	0	0	0	**e=b5**
0	0	0	2	8	16	0	0	0	0	0	4	**f=b6**
0	0	3	0	0	0	22	5	0	0	0	0	**g=b7**
0	0	1	0	0	0	16	3	10	0	0	0	**h=b8**
0	0	0	0	0	0	1	0	26	3	0	0	**i=b9**
0	0	1	0	0	0	0	0	1	26	2	0	**j=b10**
0	0	0	0	0	1	0	0	1	4	21	3	**k=b11**
0	0	0	0	1	0	0	0	0	0	1	28	**l=b12**

- ***K star algorithm***

The outcome of the K star is presented in the form of confusion matrix as shown in the Table 5.9.

Table 5.9 Confusion matrix of K star algorithm for EMD features of bearing

a	b	c	d	e	f	g	h	i	j	k	l	class
26	3	0	0	0	0	1	0	0	0	0	0	**a= b1**
4	26	0	0	0	0	0	0	0	0	0	0	**b=b2**
1	1	26	0	0	1	1	0	0	0	0	0	**c=b3**
0	0	0	27	0	2	0	0	0	0	1	0	**d=b4**
0	0	0	0	10	20	0	0	0	0	0	0	**e=b5**
0	0	0	1	10	15	0	0	0	0	0	4	**f=b6**
0	0	0	0	0	0	20	10	0	0	0	0	**g=b7**
0	0	0	0	0	0	9	14	6	1	0	0	**h=b8**
0	0	0	0	0	0	0	3	26	1	0	0	**i=b9**
0	0	1	1	0	0	0	1	1	23	3	0	**j=b10**
0	0	0	0	0	1	0	0	1	2	19	7	**k=b11**
0	0	0	0	1	2	0	0	0	0	6	21	**l=b12**

From the confusion matrix, 107 instances were misclassified out of 360 instances. The overall classification efficiency was found to be 70.27%, which is lesser than random forest and SVM classifiers. Hence, the K-star model with EMD features for fault diagnosis of the bearing was not considered.

- ***Summary***

The EMD features were extracted from the acquired vibration signals and a decision tree was used to select the important features. The effectiveness of a selected set of features in the classification of faults was illustrated. Table 5.10 summarizes the classification efficiencies of various classifiers with EMD features.

Table 5.10 Classification accuracy achieved with EMD feature for different classifiers for bearing data set

Classifier	**SVM**	**Random forest**	**K star**
Classification accuracy (%)	72.77	**76.38**	70.27

In comparison to the performance of other classifiers, the random forest algorithm achieved a maximum classification efficiency of 76.38% when using EMD features.

5.3.3 Fault diagnosis using DWT features

The vibration signals were analysed using the discrete wavelet transform method. It divides the input signal into two elements: high-frequency elements and low-frequency elements. The low-frequency elements are further discretized. The DWT technique treats the high-frequency element at each discretisation step as a feature. From the acquired vibration signals, eight discrete wavelet features (v1, v2… v8) were extracted for each class of the ball bearing. Table 5.11 illustrates the discrete wavelet features obtained using the DWT; out of 30 samples, only two samples corresponding to each bearing condition are shown. These features were used as inputs to the decision tree, to select the most significant features which give the highest classification accuracy.

Table 5.11 DWT feature extracted from bearing vibration signals

Sample No.	Class	v1	v2	v3	v4	v5	v6	v7	v8
1	**Healthy**	13.1	94.7	6.12	23	10.2	28.6	93.9	143
1	**Healthy**	11.6	81.4	5.09	19.2	17.9	52.2	215	367
2	**IR fault**	1.98	3.98	4.5	4.94	8.78	48.9	230	521
2	**IR fault**	2.46	5.65	7.48	7.73	14.4	74.2	288	458
3	**OR fault**	76.6	2.82	6.36	8.89	9.05	49	179	233
3	**OR fault**	78.7	2.89	6.59	8.29	9.39	42.9	191	267
4	**IR & OR Fault**	2.88	12.9	24.2	8.95	11.1	49.1	223	491
4	**IR & OR Fault**	2.32	9.75	17.8	8.13	9.62	42.7	199	426

5.3.3.1 Feature selection by decision tree

For feature selection, the decision tree technique (J48 algorithm) was used. All the extracted wavelet features from twelve classes were fed into the algorithm, which formed the decision tree as shown in Figure 5.6. In Figure 5.6., v4 feature is a root node of the tree, based on which the tree structure is formed. When v4 value is greater than 29.5 and v5 is greater than 23.2 it is classified as healthy bearing condition at no load. When the v4 value is greater than 29.5 and v5 is less than or equal to 23.2, it is classified as healthy with T1 bearing condition and so on. Eight features such as v1, v2, v3, v4, v5, v6, v7 and v8 were selected out of eight wavelet features from the decision tree. The detailed accuracy of classification is discussed in the following section.

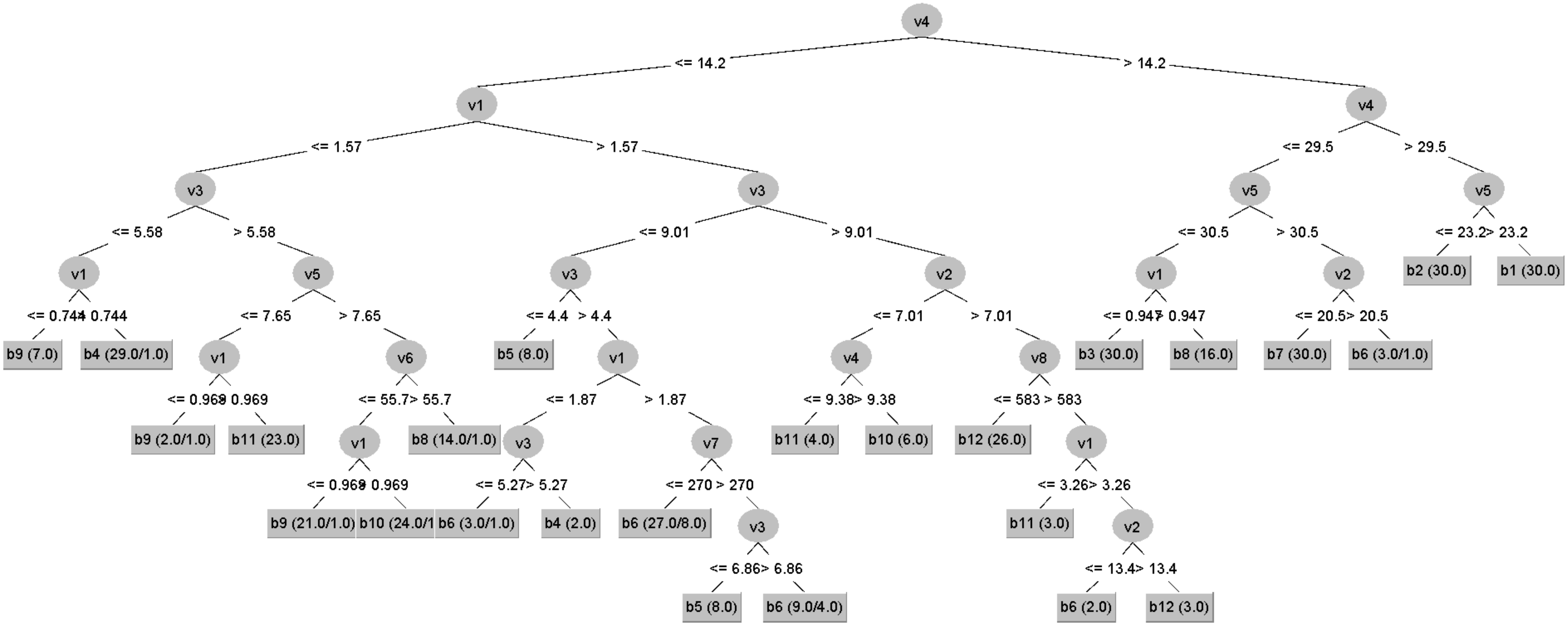


Figure 5.6 Decision tree of DWT feature of bearing data set in four stroke IC engine gearbox

5.3.3.2 Classification

The selected wavelet features were treated as an input and fed to the classifiers such as SVM, random forest and K-star models. The results obtained from the models were analysed and discussed below.

- ***K star algorithm***

The selected wavelet features, such as v1, v2, v3, v4, v5, v6, v7 and v8, were used as inputs to the K star algorithm. The confusion matrix is depicted in Table 5.12. It shows the outcome of the K star algorithm for DWT features of vibration signals.

Table 5.12 Confusion matrix of K star algorithm for DWT features of bearing

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**class**
30	0	0	0	0	0	0	0	0	0	0	0	**a= b1**
0	30	0	0	0	0	0	0	0	0	0	0	**b=b2**
0	0	30	0	0	0	0	0	0	0	0	0	**c=b3**
0	0	0	28	0	1	0	0	0	1	0	0	**d=b4**
0	0	0	1	17	12	0	0	0	0	0	0	**e=b5**
0	0	0	0	7	21	0	2	0	0	0	0	**f=b6**
0	0	0	0	0	0	29	1	0	0	0	0	**g=b7**
0	0	0	0	0	0	0	29	1	0	0	0	**h=b8**
0	0	0	0	0	0	0	0	30	0	0	0	**i=b9**
0	0	0	1	0	0	0	0	0	29	0	0	**j=b10**
0	0	0	0	0	0	0	0	0	0	29	1	**k=b11**
0	0	0	0	0	0	1	0	0	0	0	29	**l=b12**

From the confusion matrix, only 29 instances were misclassified out of 360 instances. The overall classification efficiency is found to be 91.94%, which shows better performance of K star classifier. Hence, the K-star model with DWT features can be considered for fault diagnosis of the bearing.

- ***RF algorithm***

The selected wavelet features such as v1-v8 were treated as an input to the random forest algorithm. The confusion matrix obtained by the random forest for DWT features of vibration signals is shown in Table 5.13.

From the confusion matrix, only 41 instances were misclassified out of 360 instances. The overall classification efficiency was found to be 88.61% and which can be accepted for fault diagnosis, but it is lesser than the classification efficiency

(91.44%) of the K star classifier. Thus, the combination of random forest algorithm and DWT features for fault diagnosis of the bearing is not preferable.

Table 5.13 Confusion matrix of random forest algorithm for DWT features of bearing

a	b	c	d	e	f	g	h	i	j	k	l	class
30	0	0	0	0	0	0	0	0	0	0	0	**a= b1**
0	30	0	0	0	0	0	0	0	0	0	0	**b=b2**
0	0	30	0	0	0	0	0	0	0	0	0	**c=b3**
0	0	0	28	2	0	0	0	0	0	0	0	**d=b4**
0	0	0	1	16	13	0	0	0	0	0	0	**e=b5**
0	0	0	0	10	18	0	1	0	0	0	1	**f=b6**
0	0	0	0	0	0	30	0	0	0	0	0	**g=b7**
0	0	0	0	0	0	1	25	4	0	0	0	**h=b8**
0	0	0	0	0	0	0	1	29	0	0	0	**i=b9**
0	0	0	0	0	0	0	1	1	26	2	0	**j=b10**
0	0	0	0	0	0	0	0	0	0	29	1	**k=b11**
0	0	0	0	0	1	0	1	0	0	0	28	**l=b12**

- ***SVM algorithm***

The SVM classifier is used to classify the different conditions of the bearing using selected (v1-v8) DWT features of vibration signals. The confusion matrix is the outcome of the SVM representing the classification as shown in Table 5.14.

Table 5.14 Confusion matrix of SVM algorithm for DWT features of bearing

a	b	c	d	e	f	g	h	i	j	k	l	class
30	0	0	0	0	0	0	0	0	0	0	0	**a= b1**
0	30	0	0	0	0	0	0	0	0	0	0	**b=b2**
0	0	30	0	0	0	0	0	0	0	0	0	**c=b3**
0	0	0	29	1	0	0	0	0	0	0	0	**d=b4**
0	0	0	2	28	0	0	0	0	0	0	0	**e=b5**
0	0	0	0	27	0	2	1	0	0	0	0	**f=b6**
0	0	0	0	0	0	30	0	0	0	0	0	**g=b7**
0	0	0	0	7	0	2	17	4	0	0	0	**h=b8**
0	0	0	11	2	0	0	0	17	0	0	0	**i=b9**
0	0	0	8	5	0	0	0	9	8	0	0	**j=b10**
0	0	0	19	7	0	0	0	2	1	0	1	**k=b11**
0	0	0	0	0	0	1	0	0	4	7	18	**l=b12**

From the confusion matrix, 123 instances out of 360 instances were misclassified and the classification efficiency was found to be 65.83%. As the classification efficiency is considerably low when compared to K star algorithm, SVM with DWT features for fault diagnosis of bearing is not preferable.

- ***Summary***

The DWT features were extracted from the acquired vibration signals and feature selection was performed using decision tree technique. The performances of the selected feature set in classification of faults were discussed. The summary of classification accuracies of different classifiers with DWT features is shown in Table 5.15.

Table 5.15 Classification accuracy achieved with DWT feature for different classifiers for bearing data set

Classifier	**SVM**	**Random forest**	**K star**
Classification accuracy (%)	65.83	88.61	**91.94**

Table 5.15 shows that the K star algorithm provides a maximum classification efficiency of about 91.94% with DWT features as compared to the performances of other classifiers.

5.3.4 Overall conclusion from bearing vibration signal analysis based on machine learning approach

The performance of classifiers and various feature extraction methods used in the study of bearing fault diagnosis using vibration signals is summarized in Table 5.16. Based on comparison of performance, the K star model achieved a maximum classification accuracy of approximately 91.94% when used with DWT features. The combination of K star with DWT outperforms all other classifiers using any of the feature extraction techniques listed in the Table 5.16. Also, a combination of random forest model and the DWT feature technique resulted in a classification accuracy of 88.61%, which is nearer to highest classification accuracy of 91.94 % (obtained by the K star model with the DWT features). However, the performance of the random forest model with DWT features (88.61 percent classification accuracy) can be considered for fault diagnosis, but this combination requires more computational time than the K star model with DWT features. Thus, the K star technique can be recommended for fault diagnosis of bearing vibration signals when combined with the DWT features method.

Table 5.16 Comparison of classification accuracy for various feature extraction and classifiers

Feature type	Selection of feature	Classification algorithm	Instances classified correctly	Misclassified instances	Accuracy of classification (%)
Statistical	Decision tree	K star	282	78	78.33
		Random forest	296	64	82.22
		SVM	219	141	60.83
EMD		K star	253	107	70.27
		Random forest	275	85	76.38
		SVM	262	98	72.77
DWT		**K star**	**331**	**29**	**91.94**
		Random forest	319	41	88.61
		SVM	237	123	65.83

5.4 FAULT DIAGNOSIS OF GEAR IN FOUR STROKE IC ENGINE

ML techniques are used to analyse the vibration signals and diagnose gear conditions A statistical, EMD and DWT feature extraction is carried out as precursor of ML. The decision tree algorithm is used to select significant features for classification. SVM, Random Forest and K star models are used as classifiers to diagnose the gear conditions. The steps involved in feature selection and classification are described in the subsequent sections.

5.4.1 Fault diagnosis using statistical features

Time-domain features are obtained from acquired vibration signals. Section 3.3 describes the various statistical features. Total 12 different features are computed using descriptive statistical method. Table 5.17 shows features extracted from the vibration signal. After selecting important features, classifier will classify the conditions of gear using selected features.

Table 5.17 Statistical feature extracted from gear vibration signals

Sample number	Mean	Standard error	Median	Mode	Standard deviation	Sample variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	CLASS
1	0.01	0.01	0.01	-1.93	1.45	2.11	0.06	0	11.32	-5.35	5.97	156.6	**Healthy**
2	0	0.01	-0.01	-0.77	1.4	1.97	0.45	0.09	12.57	-6.22	6.35	33.81	**Healthy**
1	-0.01	0.01	0.01	-0.27	1.49	2.21	0.08	-0.02	12.33	-6.07	6.26	-166.25	**25% defect**
2	0.01	0.01	0.29	-1.53	2.16	4.69	0.08	-0.43	16.52	-8.46	8.05	295.78	**25% defect**
1	-0.01	0.01	-0.03	0.72	1.26	1.59	0.09	0.07	10.02	-5.37	4.66	-171.26	**50% defect**
2	-0.01	0.01	-0.04	-0.44	1.29	1.65	0.21	0.07	9.73	-4.84	4.89	-246.5	**50% defect**
1	0.01	0.01	0	-1.59	1.68	2.82	0.29	0.08	19.6	-8.97	10.63	251.58	**75% defect**
2	-0.04	0.01	-0.02	0.22	2.03	4.1	0.09	-0.13	18.09	-7.97	10.12	-1003.21	**75% defect**
1	0.02	0.01	-0.06	0.34	1.59	2.54	0.69	0.2	15.24	-7.96	7.28	438.94	**100% defect**
2	0.02	0.01	-0.03	1.34	1.5	2.25	0.66	0.15	12.41	-6.25	6.17	625.46	**100% defect**

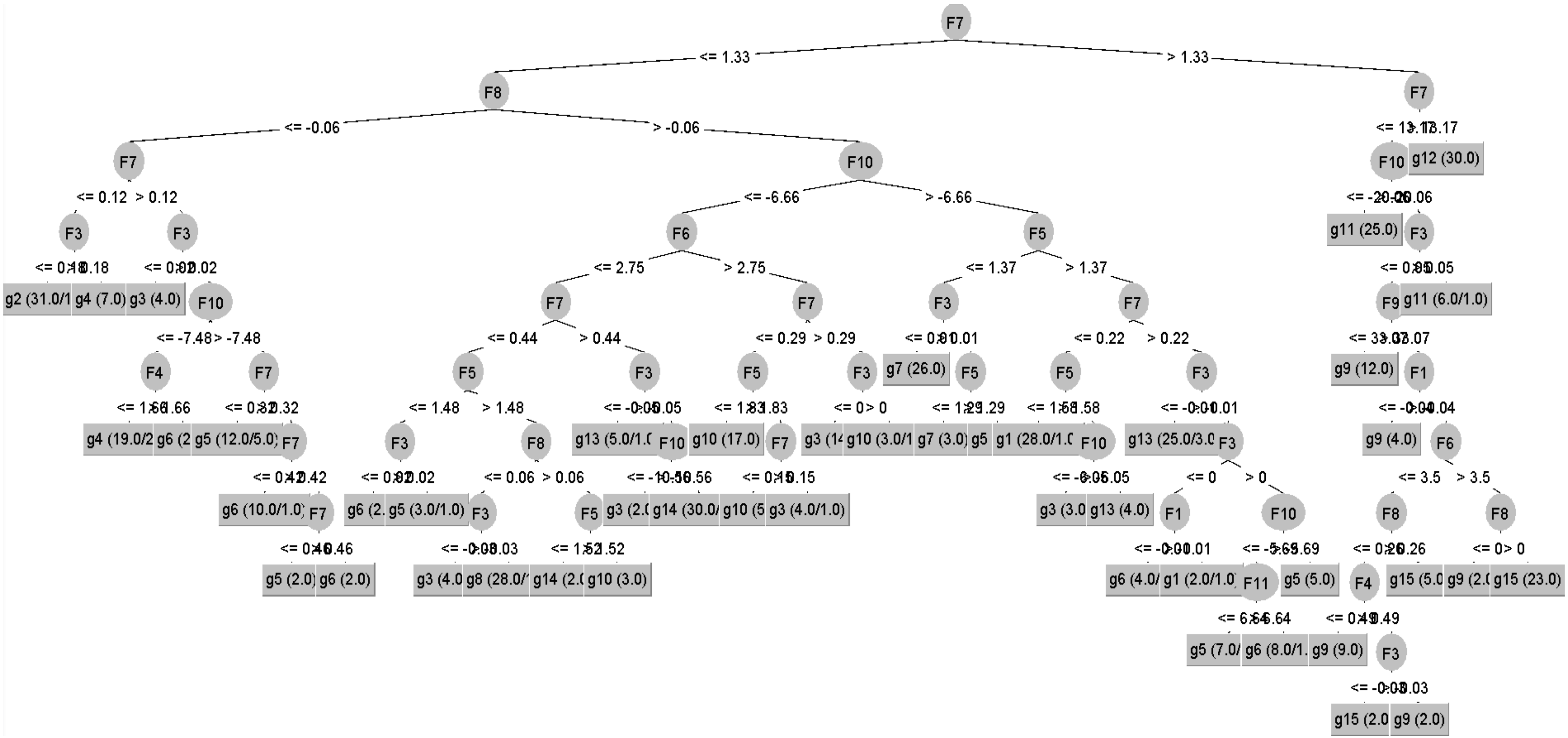


Figure 5.7 Decision tree of statistical feature of gear data set in four stroke IC engine gearbox

5.4.1.1 Feature selection using decision tree

All extracted descriptive statistical parameters were used as input to the decision tree and significant features were selected out of the extracted features. The decision tree is shown in Figure 5.7, the tree structure of different classes has been formed in such a way that when F7 is less than or equal to 0.12 and F3 is less than or equal to 0.18 value it is classified as healthy condition with T1. The gear conditions (healthy, 25% defect, 50% defect, 75% defect and 100% defect) are represented as leaves in the tree. Among 12 features, except F2 and F12 all other 10 features are selected by decision tree as most significant features. These selected features are served as input to the classifiers such as SVM, random forest and K-star algorithms. The abbreviation used in decision tree are: **g1**=Healthy gear with no load, **g2**=Healthy gear with T1 torque, **g3**=Healthy gear with T2 torque, **g4**= 25% defect gear with no load, g**5**= 25% defect gear with T1 torque, **g6**= 25% defect gear with T2 torque, **g7**= 50% defect gear with no load, **g8**=50% defect gear with T1 torque, **g9**= 50% defect gear with T2 torque, **g10**=75% defect gear with no load, **g11**= 75% defect gear with T1 torque, **g12**= 75% defect gear race with T2 torque, **g13**= 100% defect gear with no load, **g14**= 100% defect gear race with T1 torque, **g15**= 100% defect gear with T2 torque

5.4.1.2 Feature classification

In the following subsections, results obtained from the classifiers such as, random forest, SVM and K-star algorithm will be discussed and also comparative study of these classifiers will be highlighted.

- ***SVM algorithm***

The confusion matrix of the SVM model for statistical features of vibration signals are presented in Table 5.18. From the confusion matrix, out of 450 instances 203 instances were misclassified with classification efficiency of 54.88% which is very less for fault diagnosis. Hence, the SVM model with statistical features is not preferable for fault diagnosis of gear in IC engine.

Table 5.18 Confusion matrix of SVM algorithm for gear data set

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**m**	**n**	**o**	**class**
16	0	0	0	10	0	1	2	0	0	0	0	1	0	0	**a= g1**
2	20	0	0	3	1	0	4	0	0	0	0	0	0	0	**b=g2**
0	1	12	0	2	0	0	2	0	7	0	0	0	6	0	**c=g3**
2	6	0	15	3	3	0	1	0	0	0	0	0	0	0	**d=g4**
11	5	0	0	7	0	6	1	0	0	0	0	0	0	0	**e=g5**
12	8	0	1	7	0	0	2	0	0	0	0	0	0	0	**f=g6**
0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	**g=g7**
7	0	0	0	10	0	0	10	0	0	0	0	0	3	0	**h=g8**
0	0	0	0	0	0	0	0	27	0	0	0	0	0	3	**i=g9**
0	0	16	0	0	0	0	2	0	8	0	0	1	3	0	**j=g10**
0	0	0	0	0	0	0	0	1	0	29	0	0	0	0	**k=g11**
0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	**l=g12**
2	0	0	0	2	0	1	11	0	0	0	0	14	0	0	**m=g13**
2	0	0	0	7	1	0	7	0	0	0	0	0	13	0	**n=g14**
0	0	0	0	0	0	0	0	12	0	2	0	0	0	16	**o=g15**

- ***RF algorithm***

The selected statistical features such as F1, F3, F4, F5, F6, F7, F8, F9, F10 and F11 were served as an input to the random forest algorithm. The confusion matrix by the random forest for statistical features of vibration signals is shown in Table 5.19.

Table 5.19 Confusion matrix of random forest algorithm for gear data set

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**m**	**n**	**o**	**class**
26	0	0	0	2	0	0	1	0	0	0	0	1	0	0	**a= g1**
0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	**b=g2**
0	0	20	0	0	0	0	1	0	5	0	0	3	1	0	**c=g3**
1	1	0	23	1	3	0	0	0	0	0	0	0	1	0	**d=g4**
0	1	0	2	13	10	1	2	0	0	0	0	1	0	0	**e=g5**
0	0	0	4	7	17	0	1	0	0	0	0	0	1	0	**f=g6**
0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	**g=g7**
0	0	1	0	0	0	0	28	0	0	0	0	1	0	0	**h=g8**
0	0	0	0	0	0	0	0	22	0	0	0	0	0	8	**i=g9**
0	0	5	1	0	0	0	0	0	23	0	0	0	1	0	**j=g10**
0	0	0	0	0	0	0	0	0	0	27	0	0	0	3	**k=g11**
0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	**l=g12**
0	0	0	0	0	1	1	0	0	0	0	0	26	2	0	**m=g13**
0	0	0	0	0	0	0	4	0	0	0	0	0	26	0	**n=g14**
0	0	0	0	0	0	0	0	4	0	0	0	0	0	26	**o=g15**

From the confusion matrix, 83 instances were misclassified out of 450 instances. The overall classification efficiency is found to be 81.55% and hence the obtained classification efficiency can be accepted for fault diagnosis of gearbox.

- ***K star***

The confusion matrix by the K star for statistical features of vibration signals is as shown in Table 5.20.

Table 5.20 Confusion matrix of K star algorithm for gear data set

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**m**	**n**	**o**	**class**
26	0	0	0	2	0	0	1	0	0	0	0	1	0	0	**a= g1**
0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	**b=g2**
0	0	20	0	0	0	0	1	0	5	0	0	3	1	0	**c=g3**
1	1	0	23	1	3	0	0	0	0	0	0	0	1	0	**d=g4**
0	1	0	2	13	10	1	2	0	0	0	0	1	0	0	**e=g5**
0	0	0	4	7	17	0	1	0	0	0	0	0	1	0	**f=g6**
0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	**g=g7**
0	0	1	0	0	0	0	28	0	0	0	0	1	0	0	**h=g8**
0	0	0	0	0	0	0	0	22	0	0	0	0	0	8	**i=g9**
0	0	5	1	0	0	0	0	0	23	0	0	0	1	0	**j=g10**
0	0	0	0	0	0	0	0	0	0	27	0	0	0	3	**k=g11**
0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	**l=g12**
0	0	0	0	0	1	1	0	0	0	0	0	26	2	0	**m=g13**
0	0	0	0	0	0	0	4	0	0	0	0	0	26	0	**n=g14**
0	0	0	0	0	0	0	0	4	0	0	0	0	0	26	**o=g15**

From the confusion matrix, 121 instances were misclassified out of 450 instances. The overall classification accuracy is found to be 73.11%, which is lower than performance of random forest classifier. Hence, the K-star model with statistical features is not preferred for fault diagnosis of gear.

- ***Summary***

The statistical features were extracted from the acquired vibration signals and feature selection was performed using decision tree technique. The performances of the selected features in fault classification were presented. The summary of classification efficiencies of different classifiers with statistical features is shown in Table 5.21.

Table 5.21 Classification accuracy achieved with statistical feature for different classifiers for gear data set

Classifier	SVM	Random forest	K star
Classification accuracy (%)	54.88	**81.55**	73.11

Table 5.21 shows that the random forest algorithm provides a maximum classification efficiency of about 81.55% with statistical features as compared to the performances of other classifiers.

5.4.2 Fault diagnosis using EMD features

From the acquired vibration signals relating to fifteen different class of the gear, features are decomposed into IMFs using EMD. Table 5.22 represents evaluated energy feature vector (two samples per each class) using EMD method.

Table 5.22 EMD feature extracted from gear vibration signals

Sample No.	Class	E1	E2	E3	E4	E5	E6	E7	E8
1	**Healthy**	0.13	0.36	0.52	0.13	0.05	0.03	0.53	0.53
1	**Healthy**	0.13	0.45	0.57	0.15	0.05	0.2	0.44	0.44
2	**25% defect**	0.52	0.49	0.27	0.45	0.18	0.11	0.3	0.3
2	**25% defect**	0.61	0.49	0.32	0.32	0.22	0.17	0.23	0.23
3	**50% defect**	0.24	0.22	0.39	0.19	0.06	0.03	0.59	0.59
3	**50% defect**	0.28	0.19	0.29	0.18	0.06	0.06	0.62	0.62
4	**75% defect**	0.5	0.5	0.31	0.53	0.32	0.12	0.05	0.05
4	**75% defect**	0.45	0.49	0.39	0.4	0.15	0.05	0.33	0.33
5	**100% defect**	0.32	0.27	0.49	0.3	0.07	0.05	0.5	0.5
5	**100% defect**	0.2	0.17	0.33	0.11	0.03	0.05	0.63	0.63

5.4.2.1 Feature selection by decision tree algorithm

The extracted EMD features are fed to the decision tree for the selection of the best features. Figure 5.8 depicts the decision tree for EMD features of vibration signals. Here out of eight EMD features (E1-E7) are selected as significant features by decision tree.

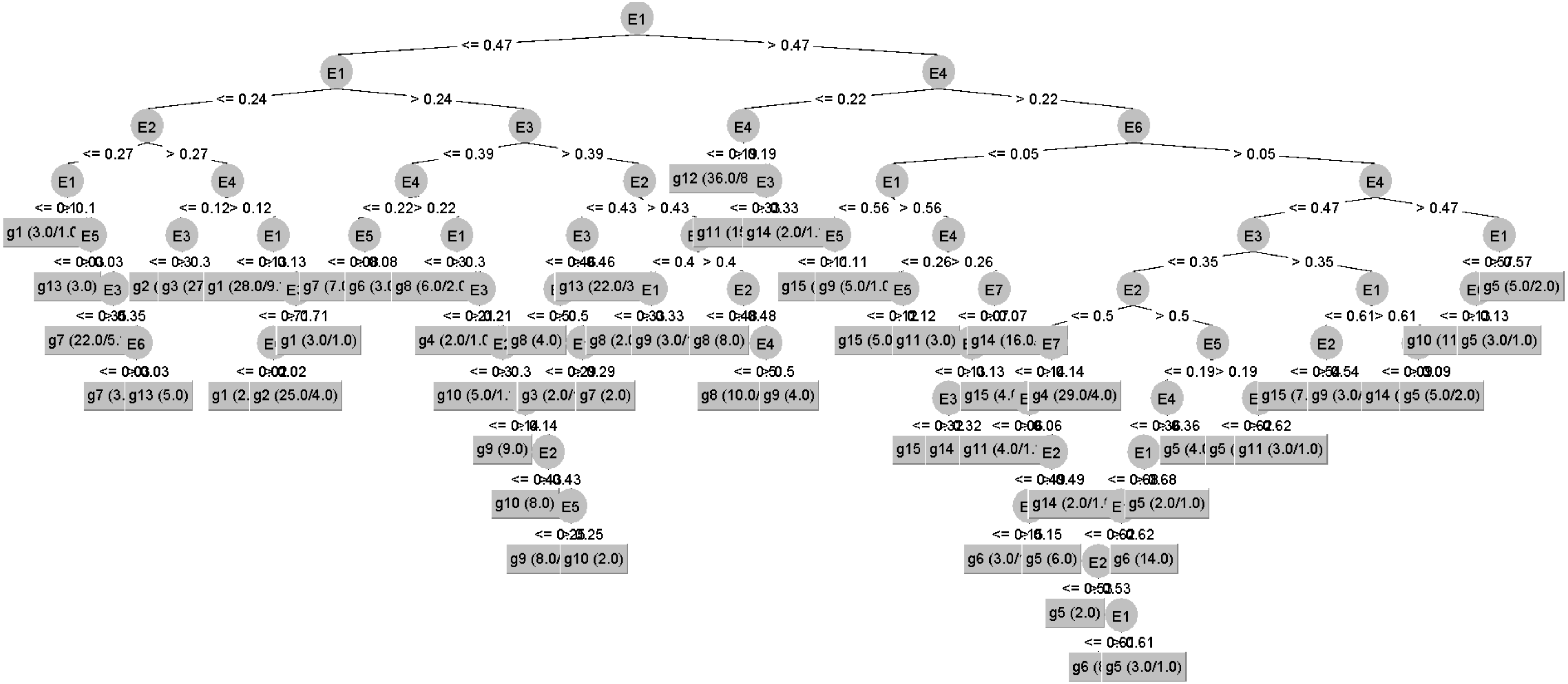


Figure 5.8 Decision tree of EMD feature of gear data set in four stroke IC engine gearbox

5.4.2.2 Feature classification

The analysis of EMD features of vibration signals using classifiers such as SVM, random forest and K star models has been carried out. The selected features such as E1-E7 for all conditions of gear are used as input to the classifiers. The classifier is tested using 10-fold cross validation method. The results obtained from each classifier in the form of confusion matrix are reported as follows.

- ***SVM algorithm***

The seven selected EMD features of vibration signals are given as an input to the SVM model. The outcome of the classifier is confusion matrix shown in Table 5.23.

Table 5.23 Confusion matrix of SVM algorithm for gear data set

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**m**	**n**	**o**	**class**
12	13	3	0	0	0	2	0	0	0	0	0	0	0	0	**a= g1**
6	14	5	0	0	0	4	0	0	0	0	0	1	0	0	**b=g2**
7	6	17	0	0	0	0	0	0	0	0	0	0	0	0	**c=g3**
0	0	0	21	4	0	1	0	0	3	0	0	0	1	0	**d=g4**
0	0	0	6	6	12	0	0	0	4	1	0	0	0	1	**e=g5**
0	0	0	4	1	24	1	0	0	0	0	0	0	0	0	**f=g6**
0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	**g=g7**
0	0	0	0	0	0	7	16	6	0	0	0	1	0	0	**h=g8**
0	0	0	0	0	1	1	7	20	1	0	0	0	0	0	**i=g9**
0	0	0	0	0	0	4	1	1	24	0	0	0	0	0	**j=g10**
0	0	0	0	2	4	0	0	0	0	10	14	0	0	0	**k=g11**
0	0	0	2	0	0	0	0	0	0	0	28	0	0	0	**l=g12**
0	0	0	0	0	0	12	3	0	0	0	0	15	0	0	**m=g13**
0	0	0	2	1	1	0	0	1	0	2	0	0	19	4	**n=g14**
0	0	0	1	0	6	0	0	1	0	1	0	0	13	8	**o=g15**

From the confusion matrix of SVM classifier with EMD features, it is found that 186 instances were misclassified and the classification efficiency is about 58.66%. The classification efficiency of SVM is very less for the fault diagnosis. Thus, SVM model with EMD features is not preferred.

- ***RF algorithm***

The confusion matrix for vibration signals of the gear is shown in Table 5.24. A data set of 450 samples consists of 30 samples from each class. From Table 5.24, out of 450 instances, 159 instances were misclassified by random forest algorithm with classification accuracy about 64.66% for the given vibration signals.

Table 5.24 Confusion matrix of random forest algorithm for gear data set

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**m**	**n**	**o**	**class**
15	10	5	0	0	0	0	0	0	0	0	0	0	0	0	**a= g1**
8	18	2	0	0	0	1	0	0	0	0	0	1	0	0	**b=g2**
6	4	20	0	0	0	0	0	0	0	0	0	0	0	0	**c=g3**
0	0	0	23	2	0	0	0	0	3	0	1	0	0	1	**d=g4**
0	0	0	3	11	9	0	0	0	3	0	0	0	1	3	**e=g5**
0	0	0	2	5	21	0	0	2	0	0	0	0	0	0	**f=g6**
0	0	0	0	0	0	26	1	0	0	0	0	3	0	0	**g=g7**
0	0	0	0	0	0	3	18	6	1	0	0	3	0	0	**h=g8**
0	0	0	0	0	0	0	6	18	4	0	0	0	0	2	**i=g9**
0	0	0	0	1	0	1	1	3	24	0	0	0	0	0	**j=g10**
0	0	0	0	1	2	0	0	0	1	19	7	0	0	0	**k=g11**
0	0	0	2	0	0	0	0	0	0	5	23	0	0	0	**l=g12**
0	2	0	0	0	0	3	4	0	0	0	0	21	0	0	**m=g13**
0	0	0	0	2	0	0	0	1	0	1	0	0	18	8	**n=g14**
0	0	0	0	2	1	0	1	3	0	0	0	0	7	16	**o=g15**

- ***K star algorithm***

K star results are presented in the form of confusion matrix as shown in the Table 5.25. From the confusion matrix, 178 instances were misclassified out of 450 instances. The overall classification efficiency is found to be 60.44%, which is lesser than random forest classifier. Hence, the K-star model with EMD features for fault diagnosis of the gear is not considered.

Table 5.25 Confusion matrix of K star algorithm for gear data set

a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	class
16	6	5	0	0	0	2	0	0	0	0	0	1	0	0	**a= g1**
10	12	7	0	0	0	1	0	0	0	0	0	0	0	0	**b=g2**
8	5	16	0	0	0	0	1	0	0	0	0	0	0	0	**c=g3**
0	0	0	24	2	1	1	0	0	1	0	1	0	0	0	**d=g4**
0	0	0	3	12	8	0	0	1	4	2	0	0	0	0	**e=g5**
0	0	0	0	5	22	0	0	1	0	0	2	0	0	0	**f=g6**
0	0	0	0	0	0	28	1	0	0	0	0	1	0	0	**g=g7**
0	0	0	0	0	0	3	14	9	1	0	0	2	0	1	**h=g8**
0	0	0	0	0	2	0	7	17	3	0	0	0	0	1	**i=g9**
0	0	0	1	1	0	1	1	4	21	1	0	0	0	0	**j=g10**
0	0	0	0	2	2	0	0	0	1	17	8	0	0	0	**k=g11**
0	0	0	0	0	1	0	0	0	0	8	20	0	0	1	**l=g12**
1	1	0	0	0	0	6	1	0	0	0	0	21	0	0	**m=g13**
0	0	0	0	1	1	0	0	1	0	1	0	0	17	9	**n=g14**
0	0	0	1	2	0	0	0	2	0	1	1	0	8	15	**o=g15**

- ***Summary***

The EMD features were extracted from the acquired vibration signals and feature selection was performed using decision tree (J48 algorithm) technique. The performances of the selected features in fault classification were presented. The summary of classification efficiencies of different classifiers with EMD features is shown in Table 5.26.

Table 5.26 Classification accuracy achieved with EMD feature for different classifiers for gear data set

Classifier	**SVM**	**Random forest**	**K star**
Classification accuracy (%)	58.66	**64.66**	60.44

Table 5.26 shows that random forest algorithm provides a maximum classification efficiency of about 64.66% with EMD features as compared to the performances of other classifiers.

5.4.3 Fault diagnosis using DWT features

From the acquired signals, DWT features were extracted and used as an input to the decision tree to select more contributing features from the derived feature vector. Eight DWT features (v1, v2, v3…..v8) for each class were extracted from the acquired 450 samples, out of which two samples from each class are displayed in Table 5.27. The steps involved in feature selection and classification are described in the subsequent sections.

Table 5.27 DWT feature extracted from gear vibration signals

Sample No.	Class	v1	v2	v3	v4	v5	v6	v7	v8
1	**Healthy**	0.107	0.716	3.46	8.72	4.32	11.6	43.1	48.7
1	**Healthy**	0.0999	0.67	3.2	8.97	4.35	9.14	32.9	48.3
2	**25% defect**	0.391	1.4	2.68	4	4.86	14.5	48.4	64.5
2	**25% defect**	0.757	2.61	3.99	5.93	9.99	32.2	105	248
3	**50% defect**	0.263	1.43	3.78	6.47	5.33	23.5	85.6	53
3	**50% defect**	0.267	1.39	3.9	6.53	5.42	23.7	88.2	60.9
4	**75% defect**	0.508	1.63	2.8	5.34	5.09	20.9	84.5	63.2
4	**75% defect**	0.658	2.18	4.04	7.28	7.39	37.3	136	81.4
5	**100% defect**	0.273	1.53	4.97	9.06	5.13	16	55.4	55.1
5	**100% defect**	0.301	1.74	5.56	10.5	6.03	24.1	77.3	57

5.4.3.1 Feature selection by decision tree

All extracted wavelet features pertaining to fifteen classes were fed to the algorithm and output is the decision tree as depicted in Figure 5.9. The rectangular blocks indicate classes (conditions) of the gear. In Figure 5.9, v3 feature is the root node of the tree, based on which the tree structure was formed. When v3 value is greater than 3.14 and v3 is less than or equal to 3.91, it is classified as a healthy gear condition with no load, when the v2 value is less than or equal to 0.94 and v3 is less than or equal to 3.14 it is classified as a healthy with T1gear condition and so on. The six features such as v1, v2, v3, v4, v5 and v8 were selected out of eight wavelet features from the decision tree. The detailed accuracy of classification is discussed in the following section.

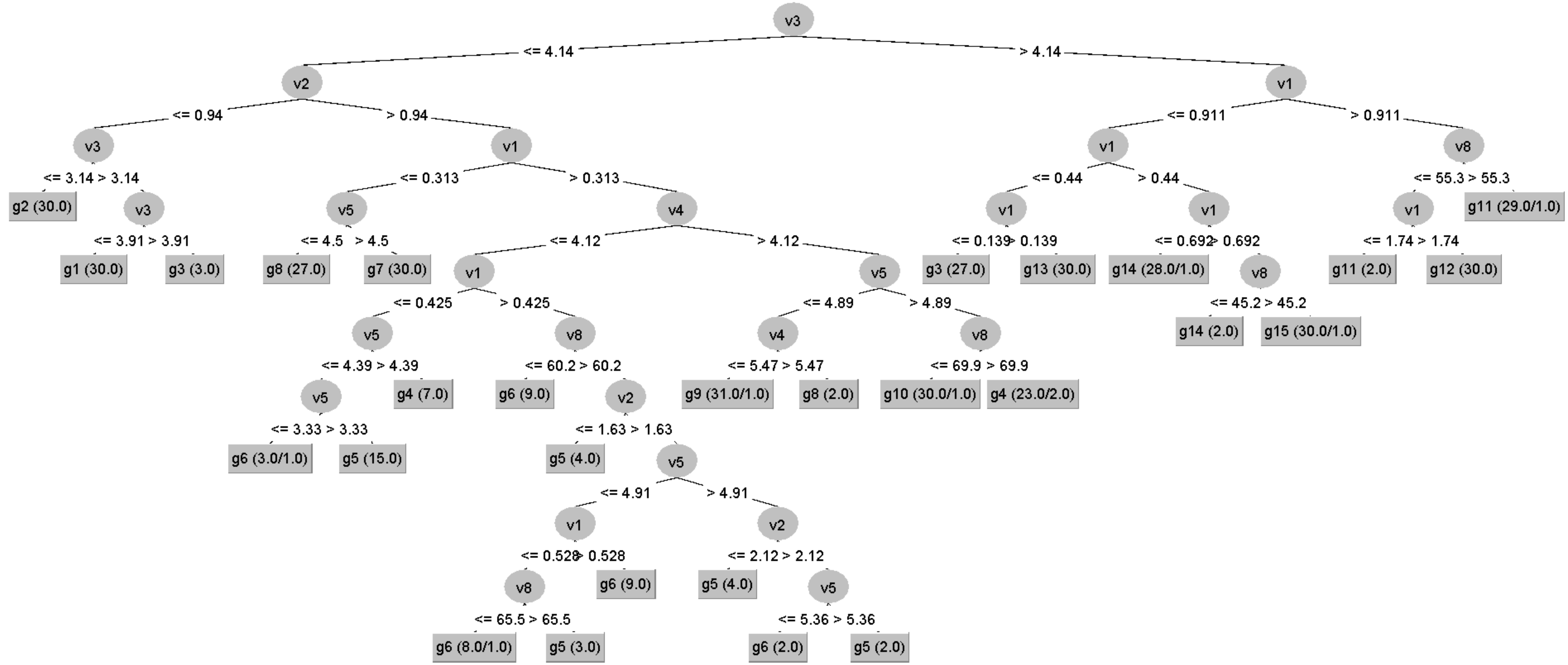


Figure 5.9 Decision tree of DWT feature of gear data set in four stroke IC engine gearbox

5.4.3.2 Classification

The selected six wavelet features were treated as an input and fed to the classifiers such as SVM, random forest and K-star models. The results obtained from the models were analysed and discussed below.

- ***K star algorithm***

The selected wavelet features such as v1, v2, v3, v4, v5 and v8 were treated as an input to the K star algorithm. The confusion matrix by the K star for DWT features of vibration signals is shown in Table 5.28.

Table 5.28 Confusion matrix of K star algorithm for gear data set

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**m**	**n**	**o**	**class**
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**a= g1**
0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	**b=g2**
0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	**c=g3**
0	0	0	29	0	0	0	0	0	1	0	0	0	0	0	**d=g4**
0	0	0	0	22	8	0	0	0	0	0	0	0	0	0	**e=g5**
0	0	0	0	5	25	0	0	0	0	0	0	0	0	0	**f=g6**
0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	**g=g7**
0	0	0	0	0	0	0	29	1	0	0	0	0	0	0	**h=g8**
0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	**i=g9**
0	0	0	1	0	0	0	0	0	29	0	0	0	0	0	**j=g10**
0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	**k=g11**
0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	**l=g12**
0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	**m=g13**
0	0	0	0	0	0	0	0	0	0	0	0	0	27	3	**n=g14**
0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	**o=g15**

From the confusion matrix, only 19 instances were misclassified out of 450 instances. The overall classification efficiency is found to be 95.77%. Hence, the K-star model with DWT features can be considered for fault diagnosis of the gear.

- ***RF algorithm***

The selected six wavelet features were treated as an input to the random forest algorithm. The confusion matrix by the random forest for DWT features of vibration signals is shown in Table 5.29.

Table 5.29 Confusion matrix of random forest algorithm for gear data set

a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	class
29	1	0	0	0	0	0	0	0	0	0	0	0	0	0	**a= g1**
0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	**b=g2**
0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	**c=g3**
0	0	0	28	1	0	0	0	0	0	0	0	0	0	1	**d=g4**
0	0	0	0	22	8	0	0	0	0	0	0	0	0	0	**e=g5**
0	0	0	1	3	26	0	0	0	0	0	0	0	0	0	**f=g6**
0	0	0	0	0	0	29	1	0	0	0	0	0	0	0	**g=g7**
0	0	0	0	0	0	0	27	3	0	0	0	0	0	0	**h=g8**
0	0	0	0	0	0	0	1	29	0	0	0	0	0	0	**i=g9**
0	0	0	1	0	0	0	0	0	29	0	0	0	0	0	**j=g10**
0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	**k=g11**
0	0	0	0	0	0	0	0	0	0	1	29	0	0	0	**l=g12**
0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	**m=g13**
0	0	0	0	0	0	0	0	0	0	0	0	0	28	2	**n=g14**
0	0	0	0	0	0	0	0	0	0	0	0	0	3	27	**o=g15**

From the confusion matrix, only 27 instances were misclassified out of 450 instances. The overall classification efficiency is found to be 94% and the obtained classification efficiency can be accepted for fault diagnosis, but it is lower than the classification efficiency (95.77%) of the K star classifier. Thus, the combination of the random forest algorithm and DWT features for fault diagnosis of the gear is not preferable.

- ***SVM algorithm***

The SVM classifier is used to classify the different conditions of the gear using selected DWT features of vibration signals. The confusion matrix is the outcome of the model representing the number of instances classified into classes as shown in Table 5.30. From the confusion matrix, 72 instances out of 450 instances were misclassified and the classification efficiency is found to be 84%. Although the classification efficiency is considerably good, but it is lower than K star and random forest algorithms. Hence, SVM with DWT features for fault diagnosis of gear is not preferable.

Table 5.30 Confusion matrix of SVM algorithm for gear data set

a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**m**	**n**	**o**	**class**
29	0	1	0	0	0	0	0	0	0	0	0	0	0	0	**a= g1**
0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	**b=g2**
1	0	29	0	0	0	0	0	0	0	0	0	0	0	0	**c=g3**
0	0	0	17	9	2	0	0	0	2	0	0	0	0	0	**d=g4**
0	0	0	0	18	12	0	0	0	0	0	0	0	0	0	**e=g5**
0	0	0	0	8	22	0	0	0	0	0	0	0	0	0	**f=g6**
0	0	0	0	0	0	21	9	0	0	0	0	0	0	0	**g=g7**
0	0	0	0	0	0	0	26	4	0	0	0	0	0	0	**h=g8**
0	0	0	0	0	0	0	2	28	0	0	0	0	0	0	**i=g9**
0	0	0	0	0	0	3	0	0	27	0	0	0	0	0	**j=g10**
0	0	0	0	0	0	0	0	0	0	29	1	0	0	0	**k=g11**
0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	**l=g12**
2	0	3	0	0	0	0	0	0	0	0	0	25	0	0	**m=g13**
0	0	0	0	0	0	0	0	0	0	0	0	0	25	5	**n=g14**
0	0	0	0	0	0	0	0	0	0	0	0	0	8	22	**o=g15**

- ***Summary***

The DWT features were extracted from the acquired vibration signals and feature selection was performed using decision tree technique. The performances of the selected features in fault classification were presented. The summary of classification efficiencies of different classifiers with DWT features is shown in Table 5.31.

Table 5.31 Classification accuracy achieved with DWT feature for different classifiers for gear data set

Classifier	**SVM**	**Random forest**	**K star**
Classification accuracy (%)	84	94	**95.77**

Table 5.31 depicts that K star algorithm has provided a maximum classification efficiency of about 95.77% with DWT features as compared to the performances of other classifiers.

5.4.4 Overall conclusion from gear vibration signals analysis based on machine learning approach

The comparison of performances of classifiers and different features extraction methods which are used in the study of fault diagnosis of the gear using vibration signals is shown in Table 5.32.

Table 5.32 Comparison of classification accuracy for various feature extraction and classifiers

Feature type	**Selection of feature**	**Classification algorithm**	**Instances classified correctly**	**Misclassified instances**	**Accuracy of classification (%)**
Statistical	Decision tree	K star	329	121	73.11
		Random forest	367	83	81.55
		SVM	247	203	54.88
EMD		K star	272	178	60.44
		Random forest	291	159	64.66
		SVM	264	186	58.66
DWT		**K star**	**431**	**19**	**95.77**
		Random forest	423	27	94
		SVM	378	72	84

From Table 5.32, it can be observed that the K star model has resulted in a maximum classification accuracy of about 95.77% with DWT features as compared to other classifiers with any feature's extraction techniques listed. Also, the combination of random forest model with DWT feature technique has provided a good classification accuracy of about 94%, which is nearer to the highest classification accuracy 95.77% (obtained by the K star model with the DWT features). However, the performance (94% classification accuracy) by the random forest model with DWT features can also be considered for fault diagnosis, but this combination takes more time to compute the performance when compared to the combination of the K star classifier and DWT features. Hence, the K star technique can be chosen as the best classifier with DWT features method and this can be suggested for fault diagnosis of the gear vibration signals.

5.5 FAULT DIANGOSIS OF BALL BEARING IN TWO STROKE IC ENGINE

The present study deals with feature extraction using statistical, EMD and DWT methods. Then feature selection using decision tree method and classification is performed using artificial intelligent techniques such as SVM, RF algorithm and K star models. Each step is explained by analysing the experimental results which can be referred in the forthcoming sections.

5.5.1 Fault diagnosis using statistical features

The information obtained from the acquired time domain data are called time-domain features. Descriptive statistical method is used for computing time domain features. Table 5.33 shows the extracted statistical features from the vibration signals for two samples of each condition of the bearing.

5.5.1.1 Feature selection using decision tree

In this analysis, 30 samples of vibration signals are acquired for healthy and different faulty conditions of the bearing. Statistical features are extracted for each sample of data. The extracted feature vector is given as input to the decision tree for selecting significant features. Figure 5.10 represents the output of the technique in tree form i.e., decision tree made by J48 algorithm and it gives three best performing features for classification such as standard error, skewness and kurtosis which are arranged in the order of rank. The classes (conditions) of bearing such as healthy and faulty are indicated by rectangle blocks. Figure 5.10 describes the tree like structure with various classes of bearing conditions identified in such a way that standard error value is less than or equal to 0.00669 and with standard error greater than 0.004858 is classified as IR defect. Standard error greater than 0.00669 with skewness value less than or equal to -0.324914 is classified as IR and OR defect while, skewness greater than -0.324914 with kurtosis greater than 5.386099 is classified as ball fault and so on. The ball bearing conditions (healthy, inner race defect, outer race defect, combined defects, ball defect) are represented as leaves in the tree.

Table 5.33 Statistical feature extracted from bearing vibration signals

Sample number	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	Class
1	0.0008	0.0046	-0.0100	-0.754	0.736	0.542	3.080	0.049	10.53	-4.99	5.53	21.71	**Healthy**
2	0.0005	0.0047	-0.0021	-0.118	0.749	0.561	2.568	0.011	10.25	-5.08	5.17	13.30	**Healthy**
1	0.0103	0.0057	0.0052	-0.325	0.918	0.843	4.286	0.079	13.64	-6.40	7.24	264.12	**IR fault**
2	0.0093	0.0059	0.0111	-0.045	0.944	0.892	3.853	0.099	15.67	-7.28	8.39	239.02	**IR fault**
1	0.0077	0.0072	0.0130	-1.060	1.146	1.312	3.921	0.021	18.77	-9.96	8.80	196.57	**OR fault**
2	0.0072	0.0074	0.0092	0.236	1.179	1.389	5.104	0.109	22.23	-10.74	11.48	183.69	**OR fault**
1	0.0065	0.0067	0.0027	-0.075	1.076	1.158	30.699	-0.541	25.61	-13.17	12.44	167.68	**IR & OR Fault**
2	0.0059	0.0068	0.0025	0.240	1.083	1.174	31.164	-0.505	25.76	-13.20	12.56	151.49	**IR & OR Fault**
1	0.0064	0.0070	0.0085	0.681	1.127	1.270	9.116	0.196	21.05	-10.39	10.66	163.55	**Ball fault**
2	0.0060	0.0073	-0.0072	-0.624	1.167	1.361	8.080	0.184	22.71	-11.42	11.29	153.27	**Ball fault**

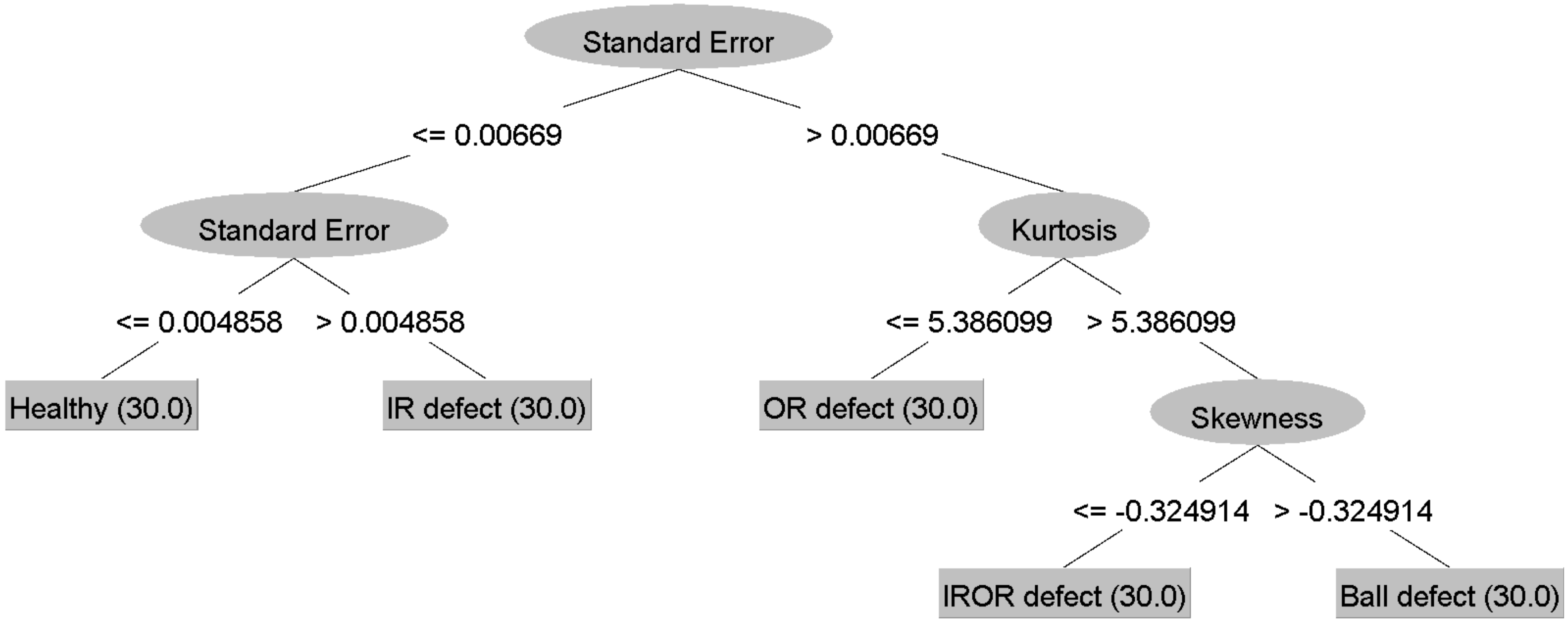


Figure 5.10 Decision tree for statistical feature of vibration signal from a two-stroke engine

5.5.1.2 Feature classification

In the following subsections, results obtained from the classifiers such as, RF, SVM and K star algorithm will be discussed and also comparative study of these classifiers will be highlighted.

- ***K star algorithm***

The selected statistical features of vibration signals were given an input to the K star algorithm. The identified classification of the bearing conditions is presented in the Table 5.34. Here, only three instances were misclassified and K star algorithm provided classification efficiency of about 98% for the given vibration signals.

Table 5.34 Confusion matrix of K star algorithm for bearing data set

a	**b**	**c**	**d**	**e**	**class**
30	0	0	0	0	**a = Healthy**
0	30	0	0	0	**b= IR defect**
0	0	29	0	1	**c= OR defect**
0	0	0	30	0	**d= IROR defect**
0	0	2	0	28	**e= Ball defect**

- ***RF algorithm***

The selected statistical features such as standard error, kurtosis and skewness were treated an input to the random forest algorithm.

Table 5.35 Confusion matrix of random forest algorithm for bearing data set

a	**b**	**c**	**d**	**e**	**class**
30	0	0	0	0	**a = Healthy**
0	29	1	0	0	**b= IR defect**
0	0	30	0	0	**c= OR defect**
0	0	0	30	0	**d= IROR defect**
0	0	1	1	28	**e= Ball defect**

The confusion matrix by the random forest for statistical features of vibration signals is shown in Table 5.35. From the confusion matrix, only 3 instances were misclassified out of 150 instances. The overall classification efficiency is found to be 98%, which is same as obtained by K star algorithm. Thus, the combination of random forest with statistical feature can be used for fault diagnosis of bearing.

- ***SVM algorithm***

The confusion matrix of the SVM model for statistical features of vibration signals are presented in Table 5.36. From the confusion matrix, out of 150 instances only 6 instances were misclassified with classification efficiency of 96% which is acceptable for fault diagnosis. However, it is less than the performance of K star and random forest (98%). Hence, the SVM model with statistical features is not preferable for fault diagnosis of bearing.

Table 5.36 Confusion matrix of SVM algorithm for bearing data set

a	**b**	**c**	**d**	**e**	**class**
30	0	0	0	0	**a = Healthy**
0	30	0	0	0	**b= IR defect**
0	0	30	0	0	**c= OR defect**
0	0	0	30	0	**d= IROR defect**
0	0	6	0	24	**e= Ball defect**

- ***Summary***

The statistical features were extracted from the acquired vibration signals and feature selection was performed using decision tree (J48 algorithm) technique. The performances of the selected features in fault classification were presented. The summary of classification efficiencies of different classifiers with statistical features is shown in Table 5.37.

Table 5.37 Statistical feature classification accuracy with different classifiers for bearing data set

Classifier	**SVM**	**Random forest**	**K star**
Classification accuracy (%)	96	**98**	**98**

Table 5.37 depicts that random forest and K star algorithms provide a maximum classification efficiency of about 98% with statistical features as compared to the performances of other classifiers.

5.5.2 Fault diagnosis using EMD features

From the acquired vibration signals relating to five different classes of the bearing faults, signals are decomposed into IMFs using EMD. Table 5.38 depicts evaluated energy feature vector (two samples per each class) using EMD method.

Table 5.38 EMD feature extracted from bearing vibration signals

Sample No.	**Class**	**E1**	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**
1	**Healthy**	0.84	0.41	0.24	0.15	0.17	0.07	0.06	0.06
1	**Healthy**	0.74	0.49	0.35	0.21	0.20	0.11	0.04	0.04
2	**IR defect**	0.87	0.35	0.25	0.16	0.14	0.07	0.02	0.02
2	**IR defect**	0.34	0.13	0.08	0.07	0.05	0.14	0.65	0.65
3	**OR defect**	0.83	0.49	0.21	0.14	0.10	0.07	0.02	0.02
3	**OR defect**	0.88	0.35	0.24	0.16	0.12	0.07	0.06	0.06
4	**IROR defect**	0.49	0.67	0.51	0.11	0.11	0.07	0.07	0.07
4	**IROR defect**	0.45	0.83	0.16	0.11	0.17	0.10	0.11	0.11
5	**Ball defect**	0.77	0.44	0.35	0.20	0.17	0.12	0.06	0.06
5	**Ball defect**	0.70	0.47	0.27	0.34	0.23	0.12	0.12	0.12

5.5.2.1 Feature selection by decision tree algorithm

All EMD features are fed to the decision tree (J48 algorithm) for the selection of the best features. Figure 5.11 depicts the decision tree for EMD features of vibration signals. Here, out of eight EMD features, 7 features (E1-E7) are selected as significant features by decision tree technique.

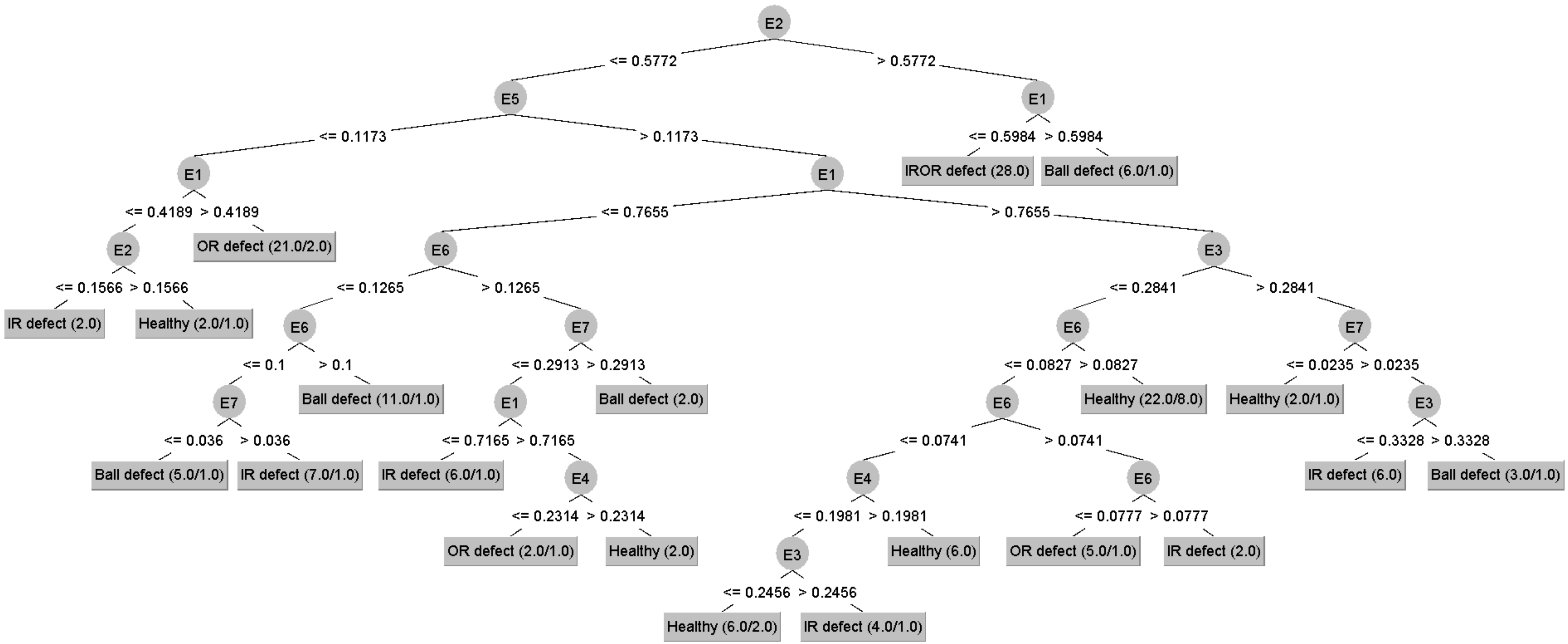


Figure 5.11 Decision tree of EMD feature of bearing data set in two stroke IC engine gearbox

5.5.2.2 Feature classification

The analysis of EMD features of vibration signals using classifiers such as SVM, random forest and K-star models has been carried out. The selected features such as E1-E7 of all conditions of a gear are used as input to the classifiers. The classifier is tested using 10-fold cross validation method. The results obtained from each classifier in the form of confusion matrix are reported as follows.

- ***SVM algorithm***

The seven selected EMD features of vibration signals are given as an input to the SVM model. The outcome of the classifier is confusion matrix shown in Table 5.39.

Table 5.39 Confusion matrix of SVM algorithm for bearing data set

a	**b**	**c**	**d**	**e**	**class**
10	2	16	0	2	**a = Healthy**
9	2	10	0	9	**b= IR defect**
3	1	24	0	2	**c= OR defect**
0	1	0	28	1	**d= IROR defect**
7	2	4	0	17	**e= Ball defect**

From the confusion matrix of SVM classifier with EMD features, it is found that 69 instances were misclassified and the classification efficiency is about 54%. The classification efficiency of SVM is very low for the fault diagnosis. Thus, SVM model with EMD features are not preferred.

- ***RF algorithm***

The confusion matrix for vibration signals of the ball bearing is shown in Table 5.40. A data set of 150 samples consists of 30 samples from each class.

Table 5.40 Confusion matrix of random forest algorithm for bearing data set

a	**b**	**c**	**d**	**e**	**class**
15	5	7	0	3	**a = Healthy**
6	12	4	0	8	**b= IR defect**
8	2	19	0	1	**c= OR defect**
0	1	0	28	1	**d= IROR defect**
7	6	2	1	14	**e= Ball defect**

From Table 5.40, out of 150 instances, 62 instances were misclassified by random forest algorithm with classification accuracy about 58.66% for the given vibration signals.

- ***K star algorithm***

The K-star results are presented in the form of confusion matrix as shown in the Table 5.41. From the confusion matrix, 88 instances were misclassified out of 150 instances. The overall classification efficiency is found to be 41.33%, which is lower than SVM and random forest classifier. Hence, the K-star model with EMD features for fault diagnosis of the bearing is not considered.

Table 5.41 Confusion matrix of K star algorithm for bearing data set

a	b	c	d	e	class
6	8	13	0	3	**a = Healthy**
6	8	9	0	7	**b= IR defect**
9	6	14	0	1	**c= OR defect**
1	0	0	24	5	**d= IROR defect**
7	10	3	0	10	**e= Ball defect**

- ***Summary***

The EMD features were extracted from the acquired vibration signals and feature selection was performed using decision tree (J48 algorithm) technique. The performances of the selected features in fault classification were presented.

The summary of classification efficiencies of different classifiers with EMD features is as shown in Table 5.42.

Table 5.42 EMD feature classification accuracy with different classifiers

Classifier	SVM	Random forest	K star
Classification accuracy (%)	54	**58.66**	41.33

Table 5.42 shows that the random forest algorithm provided a maximum classification efficiency of about 58.66% with EMD features as compared to the performances of other classifiers.

5.5.3 Fault diagnosis using DWT features

From the recorded signals DWT features were extracted and used as an input to the decision tree to select more contributing features for classification. Eight DWT features (v1, v2, v3…..v8) for each class were extracted from the acquired 150 samples, out of which two sample from each class are displayed in Table 5.43.

Table 5.43 DWT feature extracted from gear vibration signals

Sample No.	Class	v1	v2	v3	v4	v5	v6	v7	v8
1	**Healthy**	0.153	0.695	1.18	1.08	1.49	0.781	0.864	0.849
1	**Healthy**	0.159	0.713	1.31	1.14	1.84	0.684	0.818	0.511
2	**IR defect**	0.267	1.12	1.9	1.6	2.01	0.818	1.02	1.04
2	**IR defect**	0.274	1.2	1.97	1.77	1.95	0.884	1.09	1.53
3	**OR defect**	0.35	1.75	3.54	2.1	2.79	0.997	1.21	1.09
3	**OR defect**	0.363	1.78	3.79	2.27	3.37	1.24	1.25	1.14
4	**IROR defect**	0.752	1.72	1.48	1.27	1.93	0.697	0.854	0.612
4	**IROR defect**	0.736	1.78	1.49	1.5	1.89	0.66	0.813	0.586
5	**Ball defect**	0.366	1.5	3.23	2.67	3.22	1.43	1.27	0.712
5	**Ball defect**	0.368	1.71	3.36	2.66	3.75	1.46	1.41	1.23

5.5.3.1 Feature selection by decision tree

Decision tree technique (J48 algorithm) was used for feature selection. All the extracted wavelet features pertaining to five classes were fed to the algorithm and corresponding output is decision tree as depicted in Figure 5.12. The rectangular blocks indicate classes (condition) of the bearing. In Figure 5.12, v3 feature is a root node of the tree, based on which the tree structure was formed. When v3 value is less than or equal to 2.46 and v4 is less than or equal to 1.24, it is classified as a healthy bearing condition, while the v4 value is greater than 1.24 and v2 is less than or equal to 1.63, it is classified as IR defect condition and so on. The three features such as v2, v3 and v4 were selected out of eight wavelet features from the decision tree. The detailed accuracy of classification is discussed in the following section.

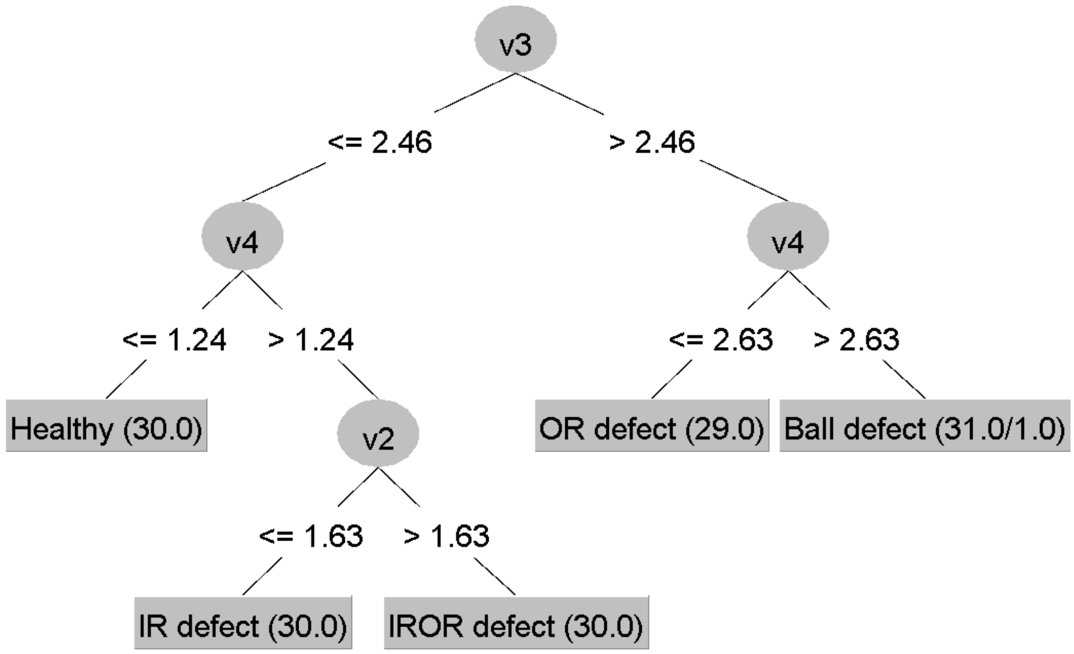


Figure 5.12 Decision tree of DWT feature of bearing data set in two stroke IC engine gearbox

5.5.3.2 Feature classification

The selected three (v2, v3, v4) wavelet features were given as an input to the classifiers such as SVM, random forest and K-star models. The results obtained from the models were analysed and discussed below.

- ***K star algorithm***

The selected wavelet features such as v2, v3 and v4 were treated as an input to the K star algorithm. The confusion matrix by the K star for DWT features of vibration signals is shown in Table 5.44.

Table 5.44 Confusion matrix of K star algorithm for bearing data set

a	**b**	**c**	**d**	**e**	**class**
30	0	0	0	0	**a = Healthy**
0	30	0	0	0	**b= IR defect**
0	0	30	0	0	**c= OR defect**
0	0	0	30	0	**d= IROR defect**
0	0	1	0	29	**e= Ball defect**

From the confusion matrix, only 1 instance was misclassified out of 150 instances. The overall classification efficiency is found to be 99.33%, which shows better performance of K star classifier. Hence, the K-star model with DWT features can be considered for fault diagnosis of the bearing.

- ***RF algorithm***

The selected wavelet features were treated as an input to the random forest algorithm. The confusion matrix by the random forest for DWT features of vibration signals is shown in Table 5.45.

Table 5.45 Confusion matrix of random forest algorithm for bearing data set

a	**b**	**c**	**d**	**e**	**class**
30	0	0	0	0	**a = Healthy**
0	30	0	0	0	**b= IR defect**
0	0	29	0	1	**c= OR defect**
0	0	0	30	0	**d= IROR defect**
0	1	0	0	29	**e= Ball defect**

From the confusion matrix, only 2 instances were misclassified out of 150 instances. The classification efficiency of 98.66% is obtained and it can be accepted for fault diagnosis, but it is lower than the classification efficiency (99.33%) of the K star classifier. Thus, the combination of the random forest algorithm and DWT features for fault diagnosis of the bearing is not preferable.

- ***SVM algorithm***

The SVM classifier is used to classify the different conditions of the gear using selected DWT features of vibration signals. From the confusion matrix in Table 5.46, 4 instances out of 150 instances were misclassified and the classification efficiency is found to be 97.33%. As the classification efficiency is considerably good it can be used for fault diagnosis. However, it is lesser than K star and random forest algorithms. Hence, SVM with DWT features for fault diagnosis of gear is not preferable.

Table 5.46 Confusion matrix of SVM algorithm for bearing data set

a	**b**	**c**	**d**	**e**	**class**
30	0	0	0	0	**a = Healthy**
0	30	0	0	0	**b= IR defect**
0	0	30	0	0	**c= OR defect**
0	0	0	30	0	**d= IROR defect**
0	0	4	0	26	**e= Ball defect**

- ***Summary***

The DWT features were extracted from the acquired vibration signals and feature selection was performed using decision tree (J48 algorithm) technique. The performances of the selected features in fault classification were presented.

The summary of classification efficiencies of different classifiers with DWT features is shown in Table 5.47.

Table 5.47 DWT feature classification accuracy with different classifiers

Classifier	**SVM**	**Random forest**	**K star**
Classification accuracy (%)	97.77	98.66	**99.33**

Table 5.47 depicts that the K star algorithm has provided a maximum classification efficiency of about 99.33% with DWT features as compared to the performances of other classifiers.

5.5.4 Overall conclusion from bearing vibration signals analysis based on machine learning approach in two stroke IC engine

The comparison of performances of classifiers and different feature extraction methods which are used in the study of fault diagnosis of the bearing using vibration signals is shown in Table 5.48.

Table 5.48 Comparison of classification accuracy for various feature extraction and classifiers

Feature type	**Selection of feature**	**Classification algorithm**	**Instances classified correctly**	**Misclassified instances**	**Accuracy of classification (%)**
Statistical	Decision tree	K star	147	3	98
		Random forest	147	3	98
		SVM	144	6	96
EMD		K star	62	88	41.33
		Random forest	88	62	58.66
		SVM	81	69	54
DWT		**K star**	**149**	**1**	**99.33**
		Random forest	148	2	98.66
		SVM	146	4	97.33

From Table 5.48, one can say that the K star model has resulted in a maximum classification accuracy of about 99.33% with DWT features as compared to other classifiers in combination with any feature extraction techniques listed in the table. Also, the combination of random forest model with DWT feature technique has provided a good classification accuracy of about 98.66%, which is nearer to the highest classification accuracy of 99.33% (obtained by the K star model with the DWT features). Hence, the performance (98.66% classification accuracy) by the random forest model with DWT features can also be considered for fault diagnosis, but this combination takes more time to compute the performance when compared to the combination of the K star as classifier and DWT features. Therefore, the K star model can be chosen as the best classifier with DWT features method and can be suggested for fault diagnosis of the bearing vibration signals.

5.6 SUMMARY

This chapter presents fault diagnosis of gearbox elements such as bearing and gear using machine learning approach based on vibration signals. This methodology involves collecting vibration signal samples for different classes or conditions of gearbox in four stroke and two stroke IC engine. From the acquired signals, features were extracted using statistical, EMD and DWT methods. J48 algorithm (decision tree) was used for significant feature selection. Artificial intelligent techniques such as SVM, K-star and random forest algorithm classifiers have been used to classify the different fault conditions. Fault diagnosis was carried out on four stroke engine data sets and two stroke engine data sets, separately. The detailed classification accuracy with different features and classifiers are shown in Table 5.16, Table 5.32 and Table 5.48. Classification accuracy was found to be reasonably good with DWT features and K star algorithm, for both bearing and gear data set in four stroke IC engine compared to other combinations of feature extraction and classifier techniques. In case of two stroke engine gearbox, statistical and DWT features performed better with all the classifiers. However, DWT feature with K star and random forest performed equally well in classifying the conditions of the bearing. Based on the results obtained, the proposed methodology with machine learning techniques can be recommended for practical applications and development of online fault diagnosis systems for IC engine gearbox condition monitoring.

CHAPTER 6

FAULT DIAGNOSIS OF IC ENGINE GEARBOX USING DEEP LEARNING TECHNIQUES

6.1 INTRODUCTION

DL is a branch of artificial intelligence used for understanding and learning about unstructured data with least intervention of the user. DL methods are used more frequently in image processing, video processing and to handle more complex data sets. The above-mentioned applications advance the use of deep learning methods for solving problems in real time. DL is an effective data feature extraction method for nonlinear large data since it can overcome the problem that shallow learning cannot extract. Although it has been successfully used in the field of speech recognition and image processing, the study of deep learning-based fault diagnosis is currently in its initial stages. This chapter describes the investigation of vibration signals of the gearbox of an IC engine based on deep learning methods used for fault diagnosis.

6.2 DEEP LEARNING METHODS

The rapid growth of internet technologies and the internet of things (IoT) has led to a significant increase in the amount of data collected compared to previous generations. Data that is increasing at an exponential rate provides more information for machine fault diagnosis, making it easier to provide accurate diagnosis results are obtained in a shorter time period. Unfortunately, fault diagnosis based on traditional machine learning theories has not been proven to be effective in large-scale data environments. It is necessary to develop some advanced DL methods in order to avoid this problem. Currently, DL methods are popular techniques and are used for feature extraction and classification. In the following sub section, DL methods and the proposed architecture are presented in detail.

6.2.1 Convolutional neural network (CNN)

CNN is a type of feed-forward neural network (NN) with convolution calculation and a deep structure (Yu et al. 2021). Initially, it was proposed for image processing by LeCun. CNNs are being used for detection, segmentation and pattern recognition in images and speech signals (Abdel-Hamid et al. 2013; Cireşan et al. 2012; Turaga et al. 2010). CNN model comprises of hidden layers and each layer extracts feature from the input signal using a filter of different kernel size with shared weights. The convolution layer of CNN extracts characteristic features from a one-dimensional (1D) input signal and maps it to the next layer as shown in Figure 6.1.

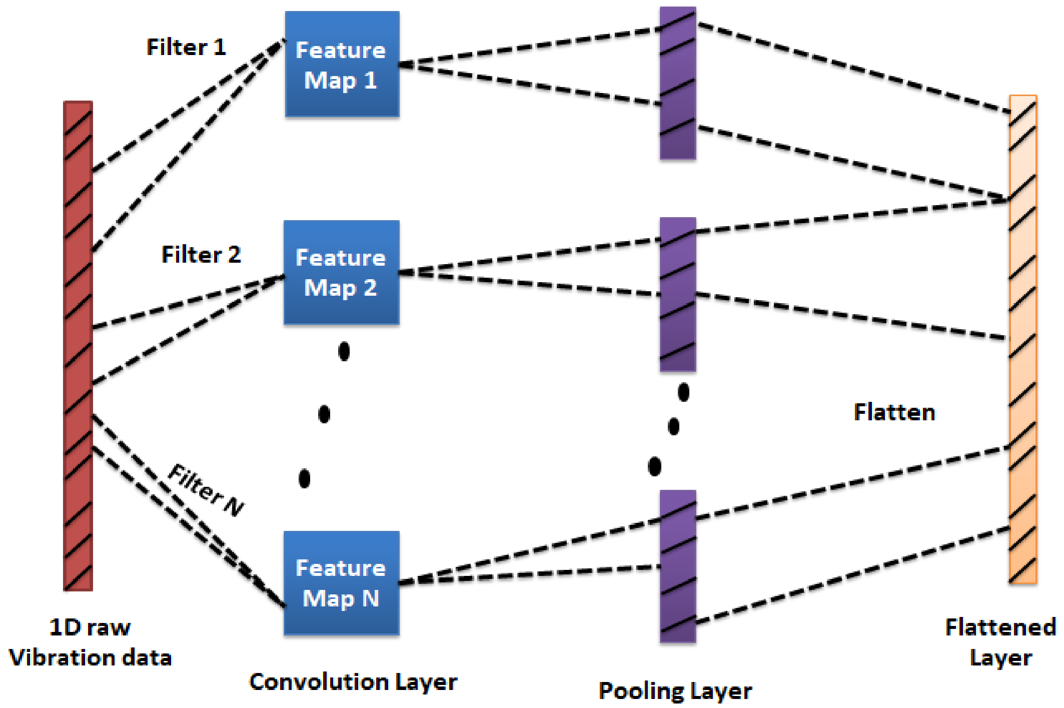


Figure 6.1 Illustration of 1D convolutional neural network

Shared weights give remarkable advantages and it reduces the computational burden in multiplex non-linear operations. The first layer of CNN is described by equation (6.1).

$$y_j^{l+1}(j) = k_i^l \times x^l(j) + b_i^l \tag{6.1}$$

where, b and k are the bias and weight for the i-th filter and l-th layer respectively, x denotes the j-th input to l-th layer and y denotes output of convolution layer. In convolution layer, Leaky-Relu activation function is used. A multiple number of filters with different kernel size are used to generate multiple features in convolution layer. The feature maps are given to the pooling layer, which extracts the dominant feature. The max-pooling layer is used to collect the largest statistic to get local features and reduce the parameters, defined by equation (6.2).

$$P_i^{l+1}(j) = \max_{(j-1)W+1 \le t \le jW} \{q_i^l(t)\} \tag{6.2}$$

where P_i^{l+1} is the result of pooling layer at i-th channel of $(l+1)$ layer and q is t-th neuron in the i-th channel and size of pooling kernel is defined as W.

6.2.2 Residual Learning

The Residual learning technique provides an easy way to do neural network training that is substantially deeper. The non-linear layer is composed of many stacked convolutional layers, batch normalization (BN) and followed by an activation layer that fits into any complex non-linear function. As the neural network layer increases, accuracy increases. However, there are limitations to the number of layers that improve accuracy. Having much deeper neural networks may not be able to learn some simple functions. As the number of hidden layers increases, accuracy may start to saturate at a certain point and eventually degrade, leading to a gradient descent problem. The residual learning block was introduced to train networks and ease reformulation of NN layers in terms of residual function with input layer and to avoid gradient descent problems(He et al. 2016a; 2016b; Peng et al. 2019). The details of residual learning are illustrated in Figure 6.2. The residual block has four significant features; (i) introducing identity skip connection, which allows flowing data directly; (ii) providing deeper network with skip connection; (iii) increasing skip connection, which does not affect much network complexity; (iv) no effect on performance with removal of layer.

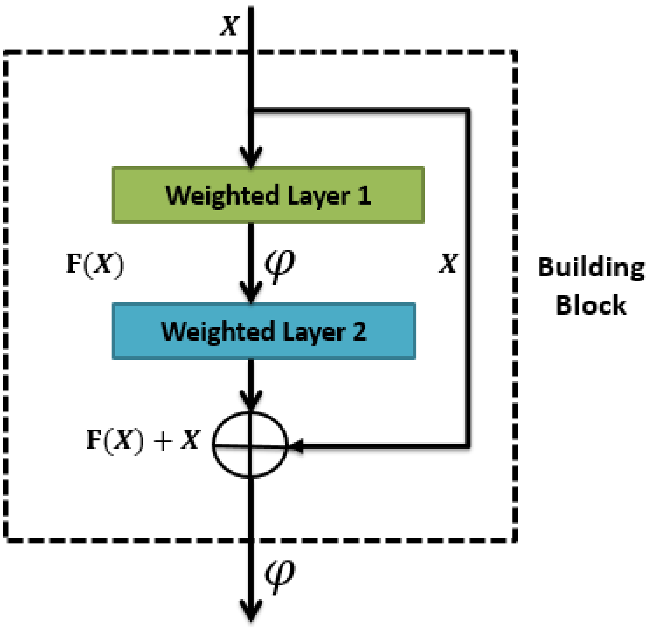


Figure 6.2 Single residual building block

Let X be the input time series data of $[x_1, x_2, x_3, \dots \dots \dots \dots \dots \dots \dots .. x_N]$, where N is the length of input data sequence, residual block can be denoted by equation (6.3).

$$y = \varphi(F(X) + X) \tag{6.3}$$

where y , φ are the output of residual learning and activation functions respectively. The operation $F(X) + X$ is calculated using identity skip connection and element-wise addition. The dimension of $F(X)$ and X must be same. Due to skip connection (X), complexity can be easily reduced, hence residual learning is a very attractive learning technique. In residual block, two weighted layers are used; weighted layer 1 and weighted layer 2. The output of the first weighted layer is given to a non-linear activation function φ before passing to weighted layer 2.

6.2.3 Dropout

Dropout is a kind of regularization technique used to avoid overfitting (Sun et al. 2016). Regularization is a type of modification taken in NNs (or any learning algorithm) to reduce generalization error, but not training error. In DL, dropout and L2 regularization techniques are adopted for reducing the error.

During dropout at every iteration, a few nodes are randomly selected, which are terminated along with incoming and outgoing node connections. After applying dropout, there is less gap between training and testing accuracy, thus providing excellent performance of neural networks. In proposed network, dropout layer is used with 0.5 probabilities, which avoids taking same feature vector of vibration signal. Probability of 0.5 implies, 50 percent neurons are selected during forward propagation and remaining 50 percent neuron are set to zero in each training epoch. However, dropout is turned off during testing process and hidden neurons of NNs are considered during testing process. In this way, NNs increase the robustness of network model, while improving the feature extracting capability of deep neural network.

6.2.4 Softmax Classifier

Fully connected (FC) layer and classifier layer are generally implemented on the top of NNs layer for classification tasks as shown in Figure 6.1 (Lei et al., 2016). The information extracted from a number of hidden layers of the network is taken as input to softmax classifier followed by backpropagation optimization. The softmax classifier is employed to diagnose GB fault and is used just before the output layer. The softmax function divides output of neurons into a distribution of probability over each fault of GB. In classifier layer, softmax calculates probability with respect to j^{th} neuron and is defined as,

$$q(z_j) = softmax(z_j) = \frac{e^{z_j}}{\sum_{k=1}^{N} e^{z_k}} \tag{6.4}$$

where z is the output from jth neuron and N is the number of gear box faults.

6.2.5 Long short-term memory

Long short-term memory (LSTM) is an improved version of recurrent neural network (RNN), which can collect entire history of the input data (Yu et al. 2019). LSTM has the same cell architecture as traditional RNN; it also contains constructive systems with gating units to control the flow of information, as shown in Figure 6.3. RNN works well when dealing with short-term dependencies. However, RNN has some shortcomings, like gradient descent and gradient explosion. To solve the problem, LSTM model is used with three gates; Input gate, Output gate and Forget gate.

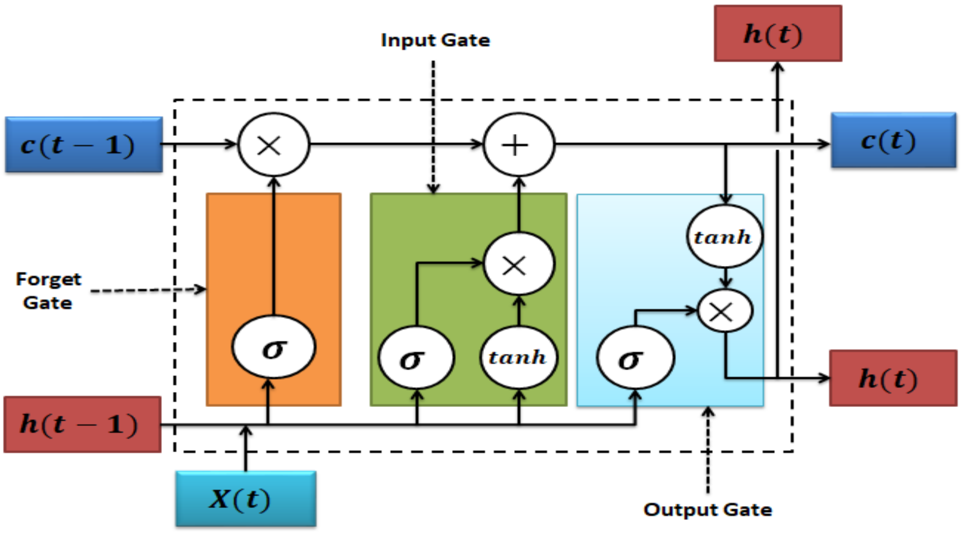


Figure 6.3 Internal structure of LSTM model

The input vibration signals are in the form of time-series data. LSTM networks are a kind of RNN that uses special units in addition to standard units. LSTM units include a 'memory cell' architecture that can maintain information in memory for a long period of time. Three gates are used to control when information is entered into the memory, when it is output and when it is forgotten. This architecture lets learn long-term dependencies and LSTM can add or remove information to cells regulated by three gates, thus providing better classification accuracy.

The input gate decides whether an input x^t and output of the previous layer h^{t-1} is given to the current cell state or not, which means the important information is added to the cell state and that are not important or redundant are removed. The forget gate is responsible for deleting information from the cell state that is not required for LSTM, which has less importance or to understand the things and are removed by a sigmoid function. Forget gate is related to the hidden cell state and current input state. The next gate is the output gate. It is responsible for generating the output based on the previous cell state and it controls the weight of output cell. The final output of LSTM depends upon previous output information and current information. Therefore, LSTM overcomes the gradient descent problem.

The mathematical expression of input gate, forget gate and output gate are given in following equations (6.5) to (6.7) respectively,

$$i^t = \sigma(W^i x^t + V^i h^{t-1} + b^i) \tag{6.5}$$

$$f^t = \sigma(W^i x^t + V^i h^{t-1} + b^f) \tag{6.6}$$

$$o^t = \sigma(W^o x^t + V^o h^{t-1} + b^o) \tag{6.7}$$

where W and V are the weights of input and hidden state respectively, b^i, b^f, b^o are the biases for input, forget and output gate respectively. The t denotes the updating step of input gate, i, output gate, o and forget gate, f, hidden state, h and cell state, c. The expression for cell state and hidden state are expressed in equation (6.8) and (6.9).

$$c^t = f^t \odot c^{t-1} + i^t \odot \tanh(W^c x^t + V^c h^{t-1} + b^c) \tag{6.8}$$

$$h^t = o^t \odot \tanh(c^t) \tag{6.9}$$

6.2.6 Adam optimizer

Adam is a first-order gradient descent optimization algorithm based on adaptive learning designed to train neural networks (Kingma and Ba 2015). Adam optimizer is more efficient than other optimizers like stochastic gradient descent (SGD), AdaGrad and RMSprop, etc. and Adam is used in this study to train deep neural networks to get the minimum value of cost function (Duchi et al. 2012). Different optimization algorithms are suitable for networks and finding the appropriate algorithm requires theoretical analysis and a trial and error-based approach in multiple cases. Adam optimizers are a combination of RMSprop and momentum with necessary modifications and it directly operates on the first-order moment of gradient descent. Hence Adam is better than other optimizer algorithms(Goodfellow et al. 2017).

6.3 DATA SET

Two datasets are used from experimental setup, one is bearing condition dataset and other is gear condition dataset of the gearbox. The performance of deep learning model is evaluated on both datasets. Here, a total of 11 trials are investigated to minimize randomness of accuracy. To reduce number of neural network parameters, sensor signals are down-sampled before giving to the model, by selecting a single data point out of two data points. Hence, out of 2000 data points only 1000 data points are considered per sample for bearing and gear datasets as shown in Figure 6.4 and Figure 6.5 respectively.

After applying down-sampling, vibration data reflects the attributes and properties of input sensor data. The amount of input datasets is reduced. After observing acceleration characteristics, it is very difficult to identify gearbox faults. Hence, in this analysis, an intelligent fault diagnosis method is proposed to diagnose the gearbox fault.

Input datasets are divided into training and testing datasets (70% for training and 30% for testing of total input data), before giving to deep learning model. Table 6.1 provides datasets of bearing of an IC engine gearbox and Table 6.2 provides datasets of 2nd gear of IC engine gearbox.

Table 6.1 Details of the bearing datasets of IC engine gearbox

Gearbox defect	**Label**	**Load type**	**No. of samples**	**Data length**	**Sensor Position**
Inner (IR) defect	0	No load	380	2000	On Gear box casing
Inner race defect	1	Load1	380	2000	
Inner race defect	2	Load2	380	2000	
Outer race (OR) defect	3	No load	380	2000	
Outer race defect	4	Load1	380	2000	
Outer race defect	5	Load2	380	2000	
IR and OR defect	6	No load	380	2000	
IR and OR defect	7	Load1	380	2000	
IR and OR defect	8	Load2	380	2000	
Healthy state	9	No load	380	2000	
Healthy state	10	Load1	380	2000	
Healthy state	12	Load2	380	2000	

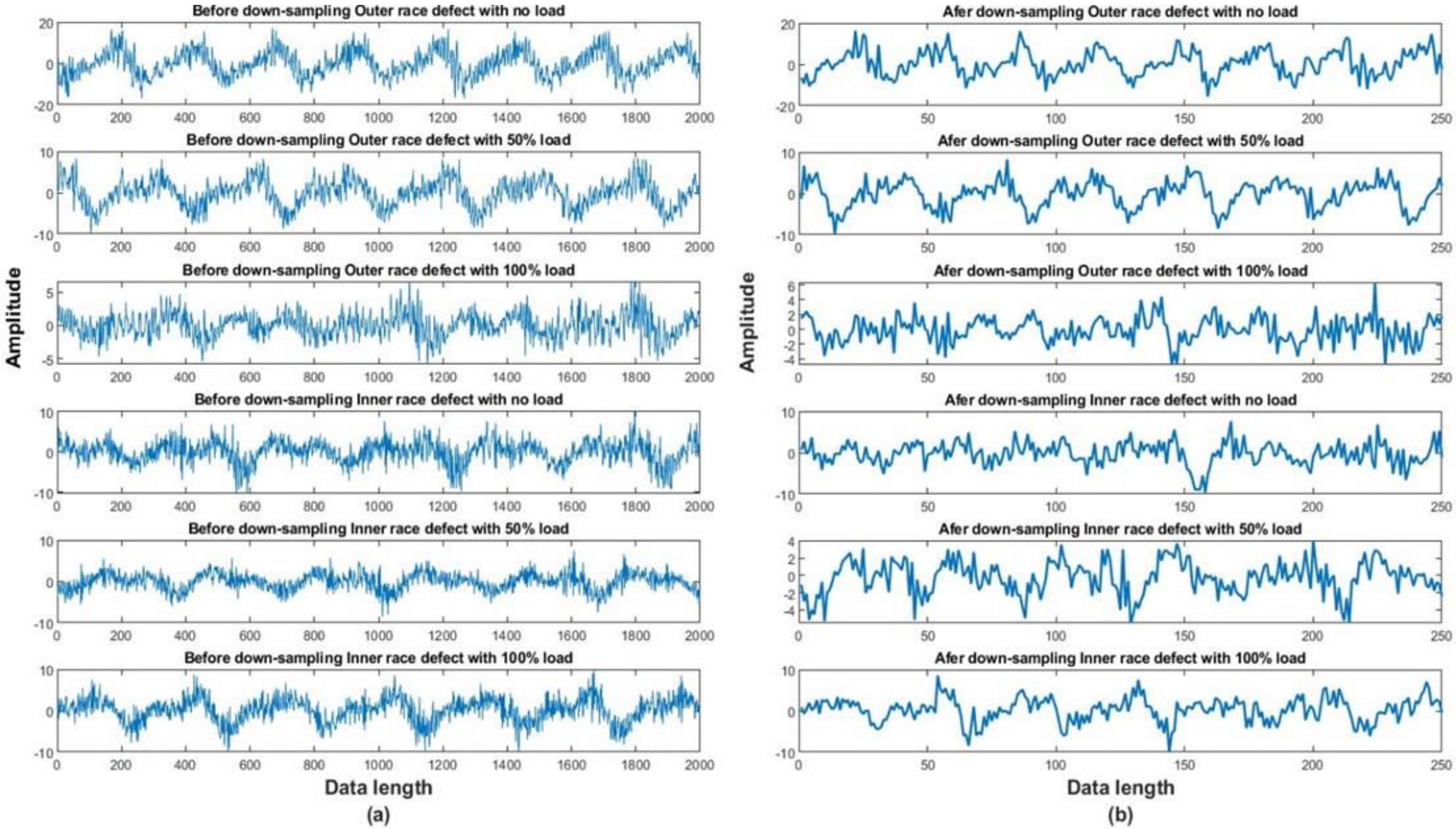


Figure 6.4 (a) Vibration signal before applying down-sampling and (b) after applying down-sampling of bearing data

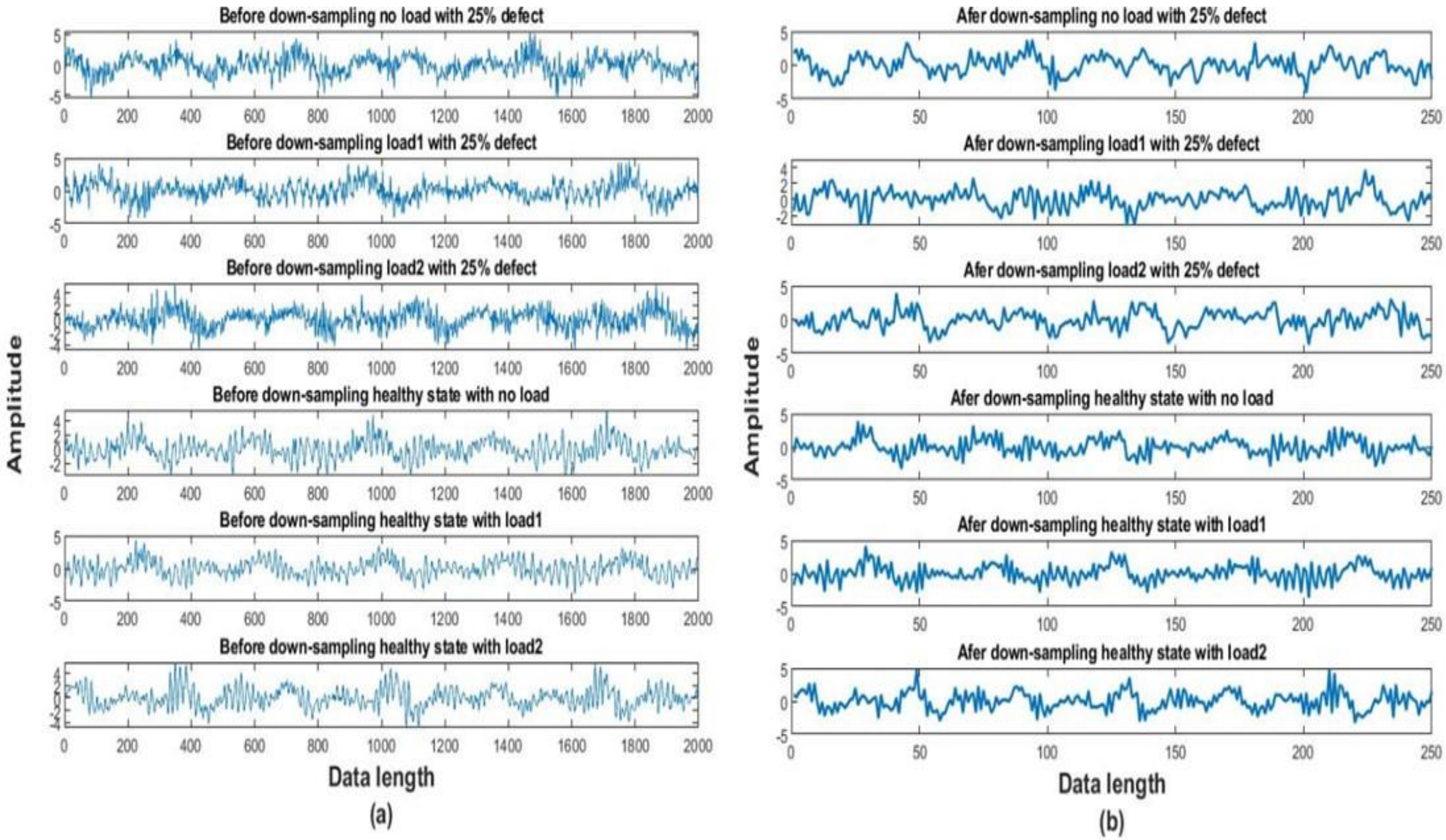


Figure 6.5 (a) Vibration signal before applying down-sampling and (b) after applying down-sampling of gear data

Table 6.2 Details of gear datasets of IC engine gearbox

Gearbox defect	**Label**	**Load type**	**No. of samples**	**Data length**	**Sensor Position**
25% gear defect	0	No load	380	2000	On Gear box casing
25% gear defect	1	Load1	380	2000	
25% gear defect	2	Load2	380	2000	
50% gear defect	3	No load	380	2000	
50% gear defect	4	Load1	380	2000	
50% gear defect	5	Load2	380	2000	
75% gear defect	6	No load	380	2000	
75% gear defect	7	Load1	380	2000	
75% gear defect	8	Load2	380	2000	
100% gear defect	9	No load	380	2000	
100% gear defect	10	Load1	380	2000	
100% gear defect	11	Load2	380	2000	
Healthy state	12	No load	380	2000	
Healthy state	13	Load1	380	2000	
Healthy state	14	Load2	380	2000	

6.4 FAULT DIAGNSOIS USING CNN AND RESIDUAL LEARNING

6.4.1 Fault diagnosis architecture of model-I using CNN and residual learning

The methodology followed in the fault diagnosis is given in Figure 6.6 and is described below in detail. Raw vibration signal from gearbox of an IC engine is considered without any signal processing techniques. To start learning process, training datasets are given as an input to the architecture. Features are extracted from the input signals using multiple layers of deep neural networks. The extracted feature maps or vectors are given to the softmax classifier for fault classification. The categorical cross-entropy function is considered as a multi-class loss function; to check systems performance in terms of predicting correct outcome. The loss function converts learning problem into an optimization problem and tries to minimize this loss function. The proposed model adopts a categorical cross-entropy loss function for multi-class classification and is defined by equation (6.10).

$$L(W) = -\frac{1}{N}\sum_{i=1}^{N} [y_i \log(\hat{y}_i)] \tag{6.10}$$

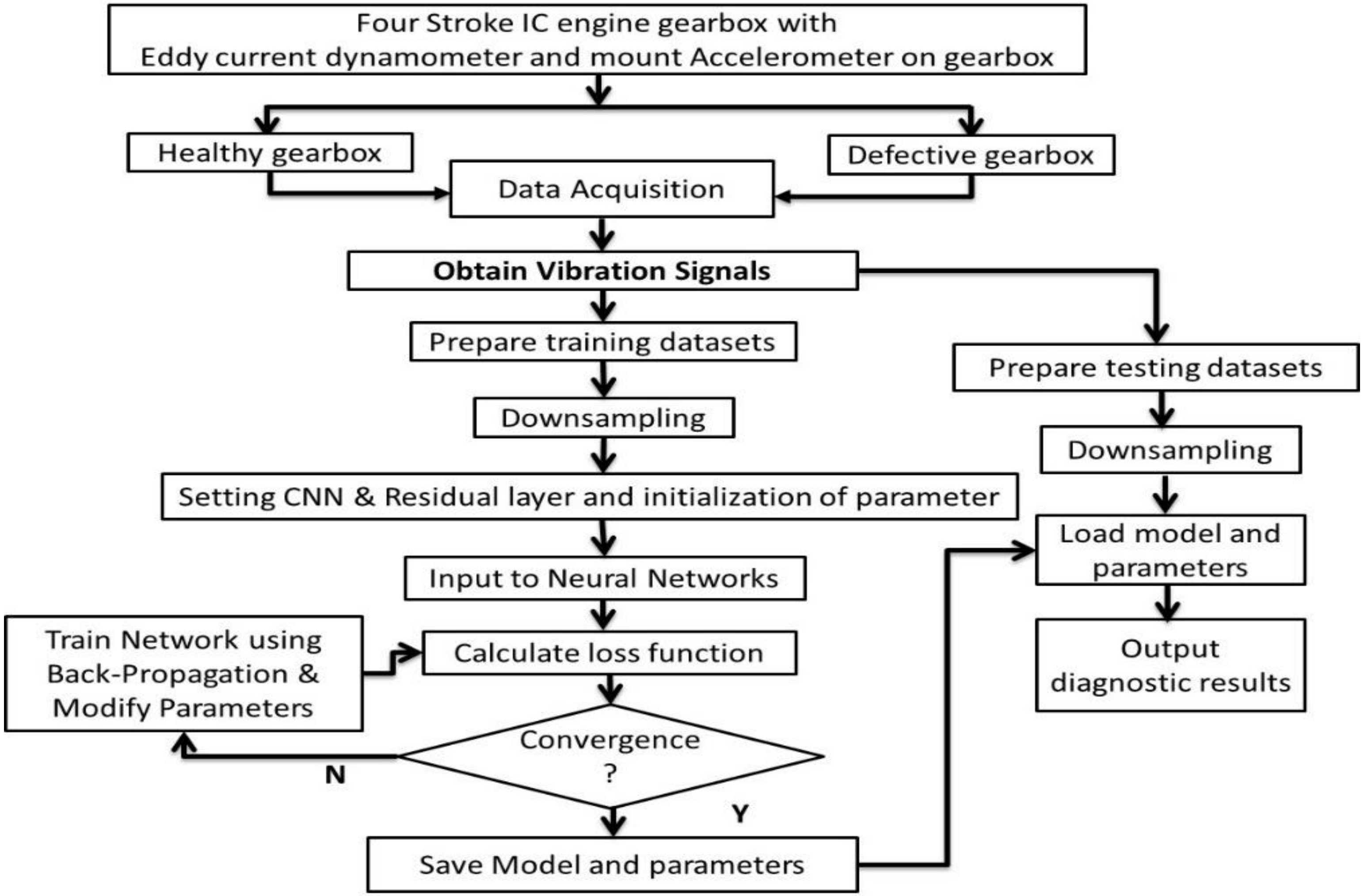


Figure 6.6 Proposed fault detection framework based on deep learning

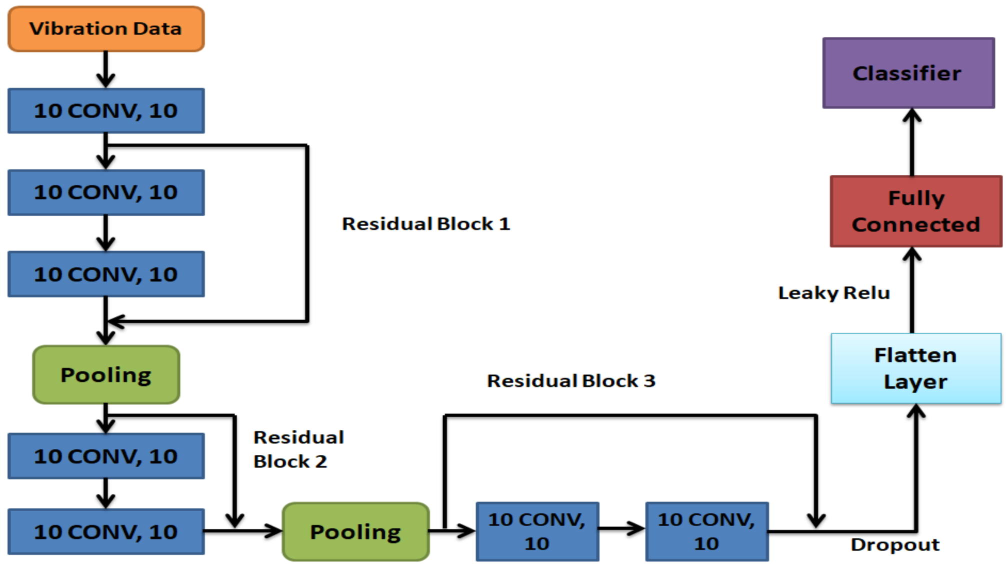
where W is model parameter, y_i and $\hat{y}_i$ are true label and predicted label respectively. Owing to loss function, it is easy to minimize errors.

Back propagation (BP) algorithm is useful for updating weight of NNs layer. Stochastic gradient descent (SGD) optimizer (Mnih et al. 2015; Schmidhuber 2015) with 0.01 learning rate is adopted to train the network for 1100 epochs and batch size of 128. In SGD, at every epoch, data samples are randomly split into many mini-batches. In general, one or two residual blocks are adopted to check model performance. Every convolutional layer in the proposed model has the same configuration (i.e., 10 filters with 10 filter length). The LeakyRelu activation function is adopted, which does not suffer from vanishing gradient problems during training process. When training is finished, test data sets are fed into the proposed model and testing accuracy of fault diagnosis is observed. In this study, an automatic feature extraction and fault detection technique for gearbox of an IC engine is proposed. Proposed model does not require any kind of pre-processing technique like data normalization (Min-max or z-score normalization). The present study allows the user to take only 1D vibration signal as an input and deep learning extracts high level features.

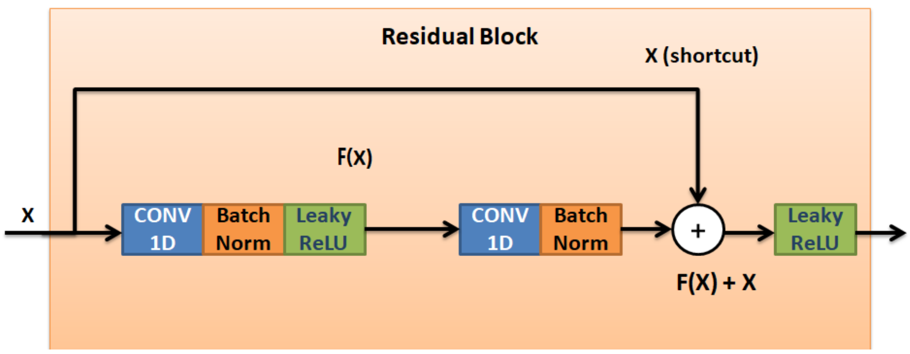
The fault diagnosis of machinery elements based on their vibration data can be divided into two main parts: feature extraction and classification. Vibration signals of elements contain considerable information related to their condition. The proposed model architecture is displayed in Figure 6.7(a). CNNs and residual learning blocks are used for high level features extraction and softmax classifier is used for classification.

In proposed fault diagnosis framework, collected 1D vibration signal is down sampled before giving to the framework, to increase calculation speed and model performance. For proposed model, there is no need of expertise in the field of signal processing or fault diagnosis. The 1D convolutional layer is the first layer of model, with F_N filter kernels window size of length F_L. Convolutional layer with different filter of same size (each filter having 10 number of filters of size 10) extracts feature maps from vibration signal. The extracted features are fed into the next layer stacked residual building block for extracting high level features.

Two weighted layers (convolutional layers) are used inside each residual block and its illustration is shown in Figure 6.7(b). The weighted layer comprises of one convolutional layer, one batch normalization (BN) and nonlinear activation function. In general, Relu and LeakyRelu activation is used as a non-linear activation function in the neural networks to avoid gradient descent problem.



(a)



(b)

Figure 6.7 (a) Proposed Fault diagnosis model (b) Illustration of residual building block

BN also known as batch norm is used to make neural network faster and increase training process. BN trains the neural networks in deep, allows user to take high learning rate and does not require initialization, which helps to eliminate use of dropout (Ioffe and Szegedy 2015). By using BN, one can achieve same accuracy with a smaller number of training steps. In architecture, two BN layers is used in each residual block. After each convolutional layer (with zero padding to get same dimension feature map) BN is used just before nonlinear activation function. LeakyRelu activation function is employed, which does not suffer from gradient vanishing problem, during training process.

Pooling layers are normally adopted to extract dominant feature from previous layer feature vectors which reduces the number of parameters and there-by increases training process. The quality of pooling layer depends on input datasets and fault diagnosis problem. These layers keep significant features from feature map. Max pooling or average pooling is considered in deep learning techniques. In this model, average pooling is adopted in between two residual learning blocks. A total of three residual building blocks are considered. Stacked residual block provides depth of feature extraction. The output of 3rd residual block is given to flatten layer and then to fully connected (FC) and softmax classifier to classify the condition of gearbox. Before giving input to flatten layer, dropout layer (probability of 0.5) is used to avoid overfitting of the model.

6.4.2 Bearing fault diagnosis using CNN and residual learning

The vibration signals of ball bearing used in this analysis is collected from GB experiment setup with four different conditions; healthy, IR defect, OR defect and combined faults at IR and OR under three loading conditions i.e., no load, load1 (9.6 Nm) and load2 (13.3 Nm) are considered for the analysis. In this analysis, there are 12 different classes of bearing data, labelled as 0 to 11, are given in Table 6.1. The model performance with different conditions of bearing under three different loading conditions are measured. Each set of raw data collected contains 25,600 data points in a single iteration and 30 iterations have been considered for each class.

Analysis is carried out with respect to different sizes of data points of each condition. Vibration signals are divided into samples with four cases: (1) 100 data points per sample; (2) 250 data points per sample; (3) 500 data points per sample; (4) 1,000 data points per sample, as shown in Figure 6.8.

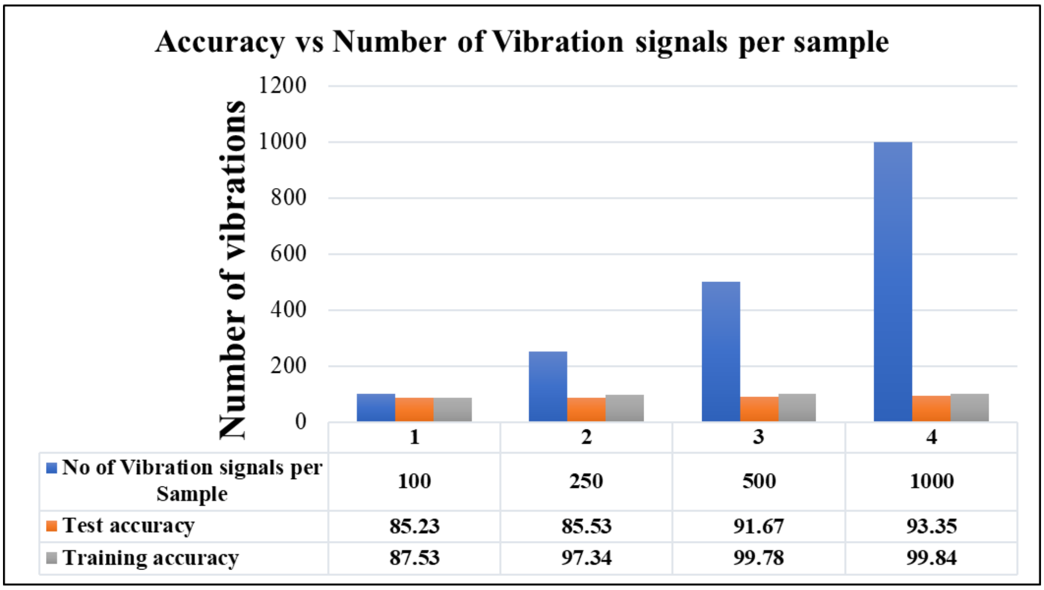


Figure 6.8 Accuracy with respect to number of vibrations

For each bearing, 380 samples are collected from accelerometer sensor and for each load condition, data is segmented into (380, 1000) shape. Input data is split into training and testing samples, 70% for training and 30% for testing. The training samples are fed into proposed model for feature extraction. After training, testing samples are input to the model for diagnosing bearing faults.

6.4.2.1 Model design

Several parameters of CNN and residual learning including; convolutional layers, activation function, pooling layers, dropout layer, residual block, flatten layer and FC layer are investigated. In the FC layer, 120 neurons are used for classification and stochastic gradient descent (SGD) optimizer with 0.01 learning rate is adopted to train the network for 1100 epochs with batch size of 128.

6.4.2.2 Results

Figure 6.9 shows the training and testing accuracy for 11 trials. It exhibits training accuracy of nearly 100% (more than 99.87%) and testing accuracy of up to 93%. Maximum classification accuracy achieved is 93.79%.

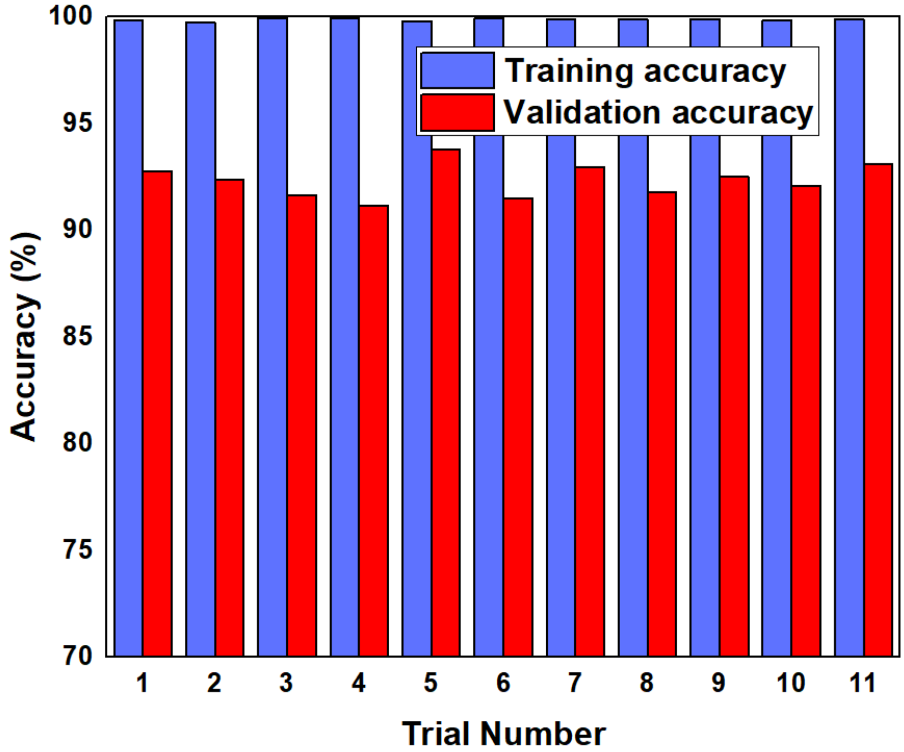


Figure 6.9 Accuracy Vs number of trials

The performance parameters like; recall, precision, F1-score and accuracy are employed for verification of the model. These are calculated by equations (6.11) to (6.14),

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{6.11}$$

$$Precision = \frac{TP}{TP+FP} \tag{6.12}$$

$$Recall = \frac{TP}{TP+FN} \tag{6.13}$$

$$F1\ score = \frac{2\times Precision\times Recall}{Precision+Recall} \tag{6.14}$$

where, TP, FP, TN and FN denotes the number of true positive, false positive, true negative and false negative respectively. These parameters are calculated through a confusion matrix that describes the classifier performance from the test data points. Further details of the evaluation of classifier parameters are given by Arslan et al. (2020). The performance parameters are calculated from confusion matrix as shown in Figure 6.10.

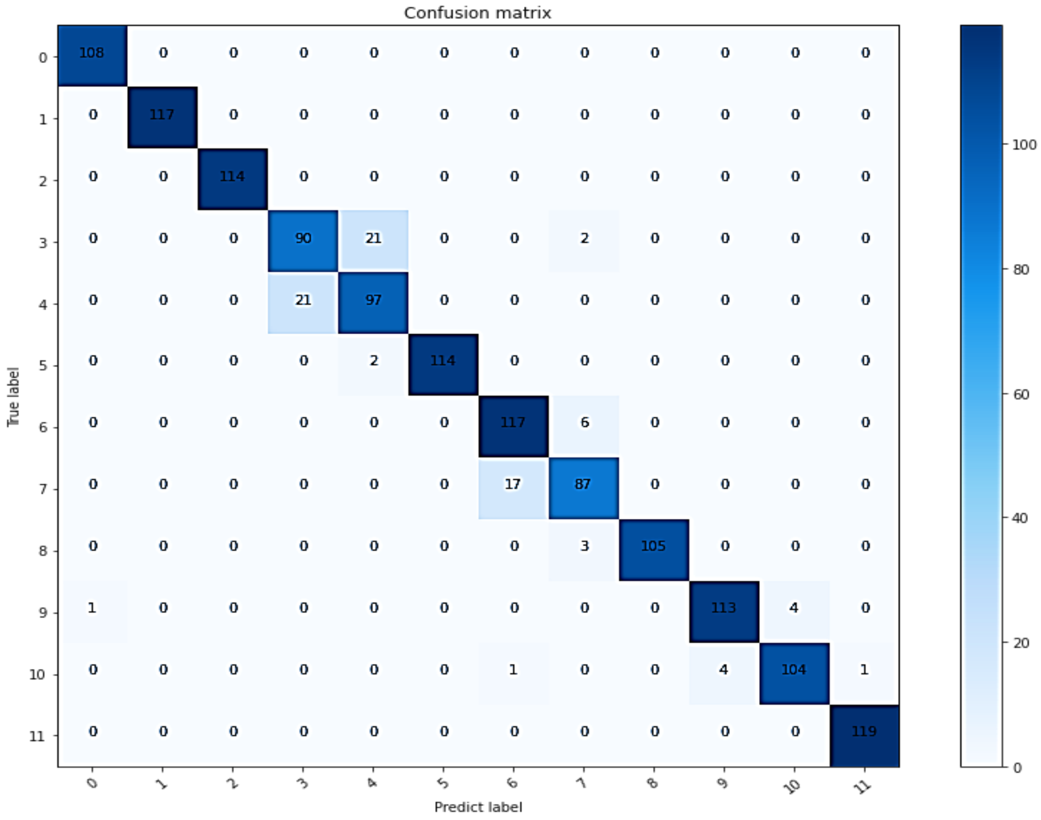


Figure 6.10 Confusion matrix of classification for the proposed model

Table 6.3 represents performance parameters with respect to bearing fault label. Lower accuracy is reason for misclassification of labels 3 to 4 and 6 to 7.

Table 6.3 Performance parameters obtained from bearing dataset

Fault label	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
0	99.08	100	99.54	99.93
1	100	100	100	100
2	100	100	100	100
3	81.08	79.65	80.36	96.78
4	80.83	82.20	81.51	96.78
5	100	98.28	99.13	99.85
6	86.67	95.12	90.70	98.25
7	88.78	83.69	86.14	97.95
8	100	97.22	98.59	99.78
9	96.58	95.76	96.17	99.34
10	96.30	94.55	95.41	99.27
11	99.17	100	99.58	99.93

This may be reason for some similarities between faulty signals. The classification becomes more difficult when there is noise in fault signals. Figure 6.11 shows variation of performance parameters with respect to number of residual blocks.

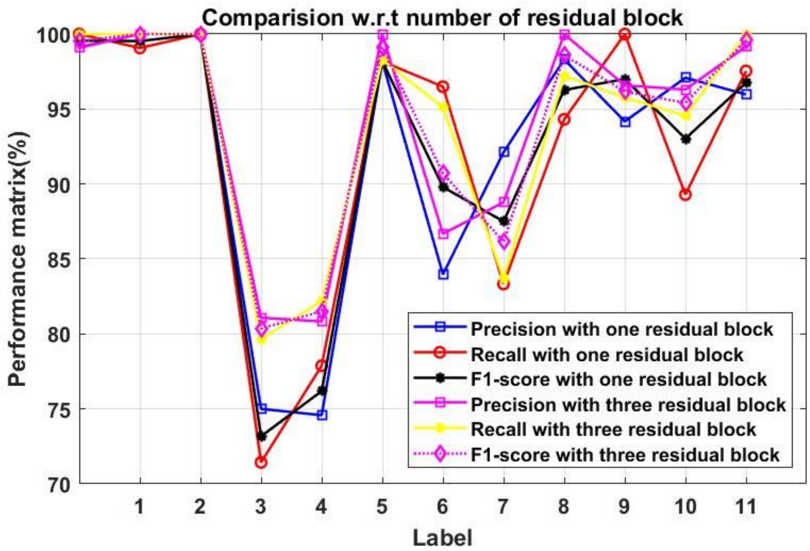


Figure 6.11 Performance matrix vs number of labels

The training and testing accuracy increase, as the number of epochs increase, as shown in Figure 6.12 and it becomes constant after 1000 epochs, as shown in Figure 6.13. The maximum accuracy achieved by the proposed model is 93.79%.

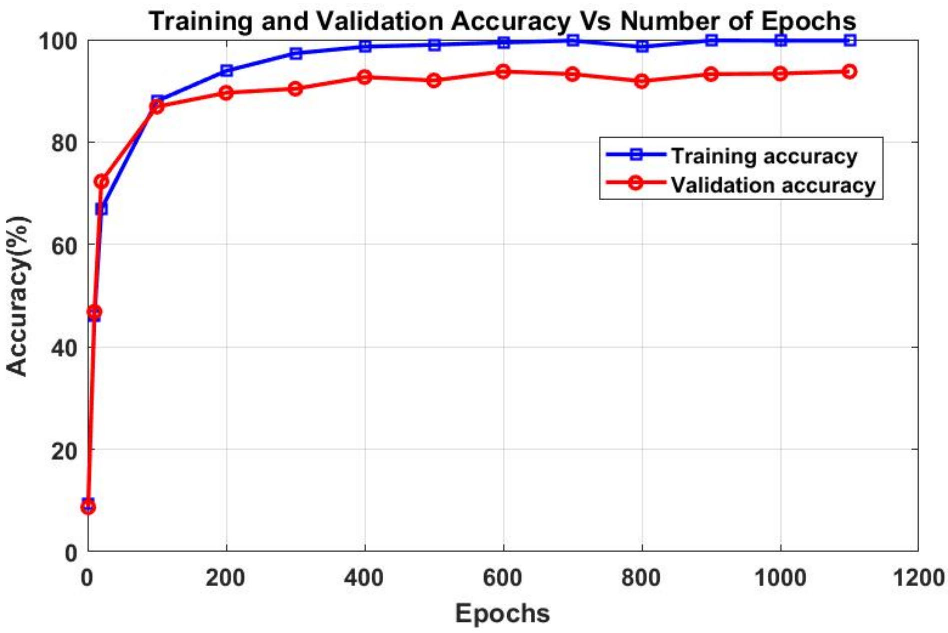


Figure 6.12 Training and testing accuracy over number of epochs for bearing fault datasets

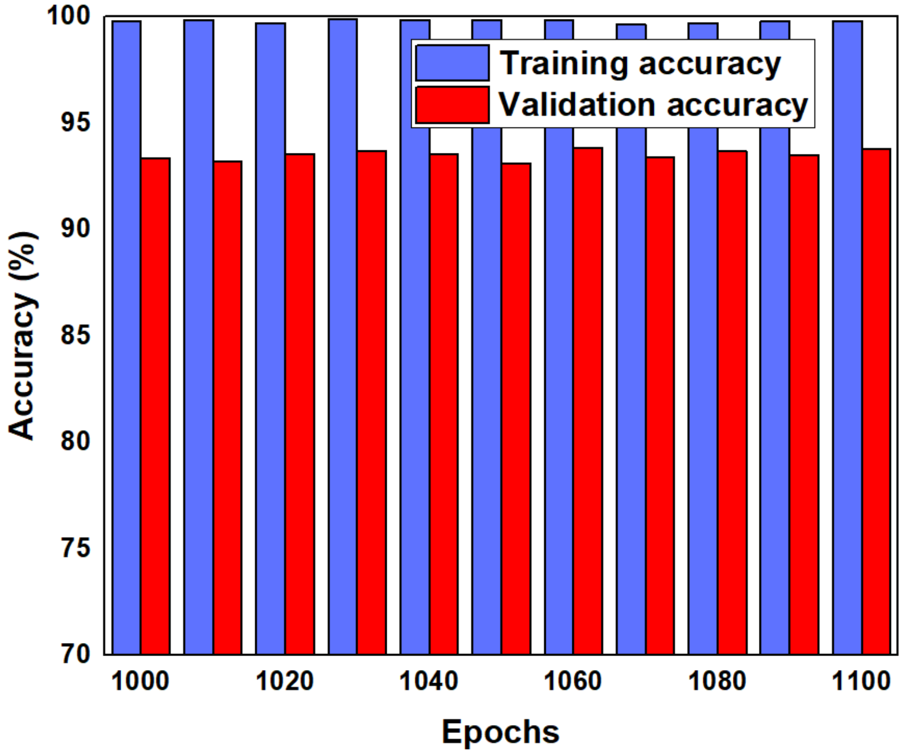


Figure 6.13 Accuracy after 900 epochs

6.4.3 Gear fault diagnosis using CNN and residual learning

In the 2nd study, gear with healthy and progressive tooth defect conditions are chosen for analysis. There are 15 different classes of gear labelled as 0 to 14, which is given in Table 6.2. The model performance is evaluated with different conditions of gear and under different loading conditions. Raw data of each trial contains 25,600 data points and 30 iteration data for each class have been used.

Similar to bearing diagnosis, investigations have been done with respect to different set of data points. Vibration signals are divided into samples and each data sample contains 1000 data points. All classes of gear datasets include 380 samples for analysis that are collected through accelerometer sensor. Input data is split into 70% for training samples and 30% for testing samples. The training samples are fed into proposed model for feature extraction after training and testing samples are given as input for fault diagnosis of gear fault.

6.4.3.1 Model design

Similar to bearing datasets, same number of layers are used for gear datasets of an IC engine gearbox. In FC layer, 150 neurons are used for classification and stochastic SGD optimizer with 0.01 learning rate is adopted to train the network for 1100 epochs with batch size of 128.

6.4.3.2 Results

Figure 6.14 shows the training and testing accuracy of 11 trials. In Figure 6.15, it can be observed that the training accuracy is near to 100% (more than 99.87%) and testing accuracy is up to 92%.

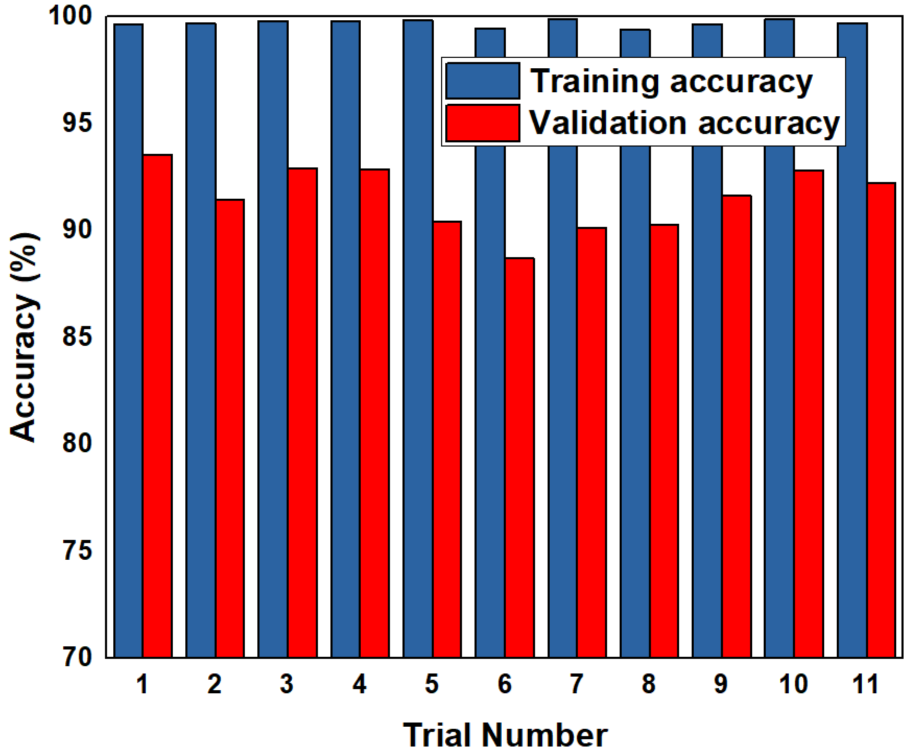


Figure 6.14 Accuracy of 11 trials for gear data set

A maximum of 92.57% classification accuracy is achieved. The performance parameters like: precision, F1-score, recall and accuracy are employed for verification of the model and is calculated from confusion matrix.

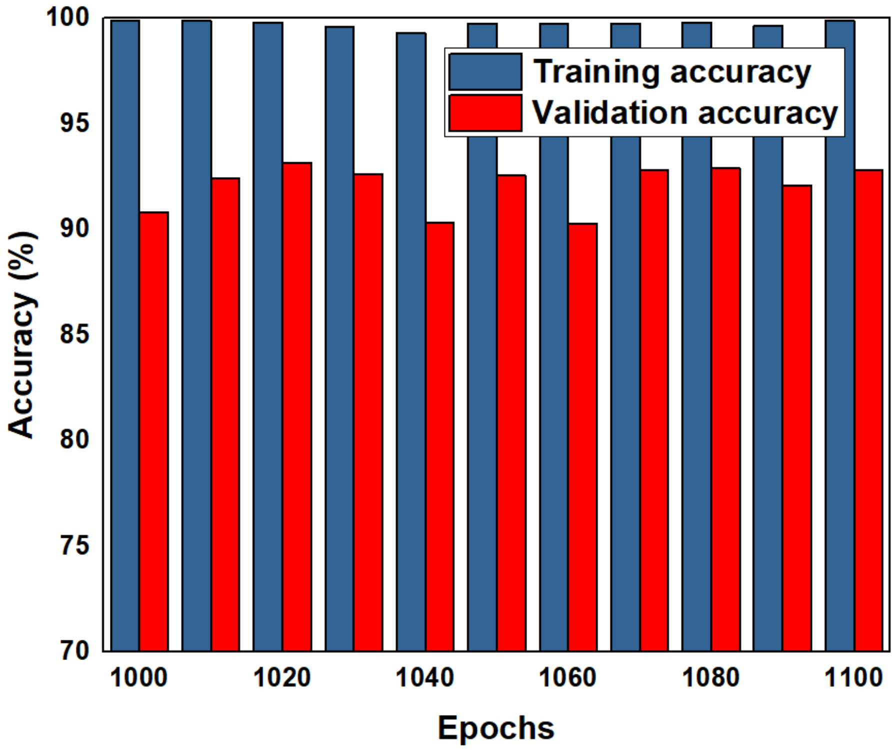


Figure 6.15 Accuracy after 900 epochs

The confusion matrix for gear data is shown in Figure 6.16. The accuracy, precision, recall and F1-score for case study II is given in Table 6.4. The lower accuracy is the reason for misclassification of labels 5 to 6 and 7 to 8 and it may also be the reason for similarities between faulty signal and noise.

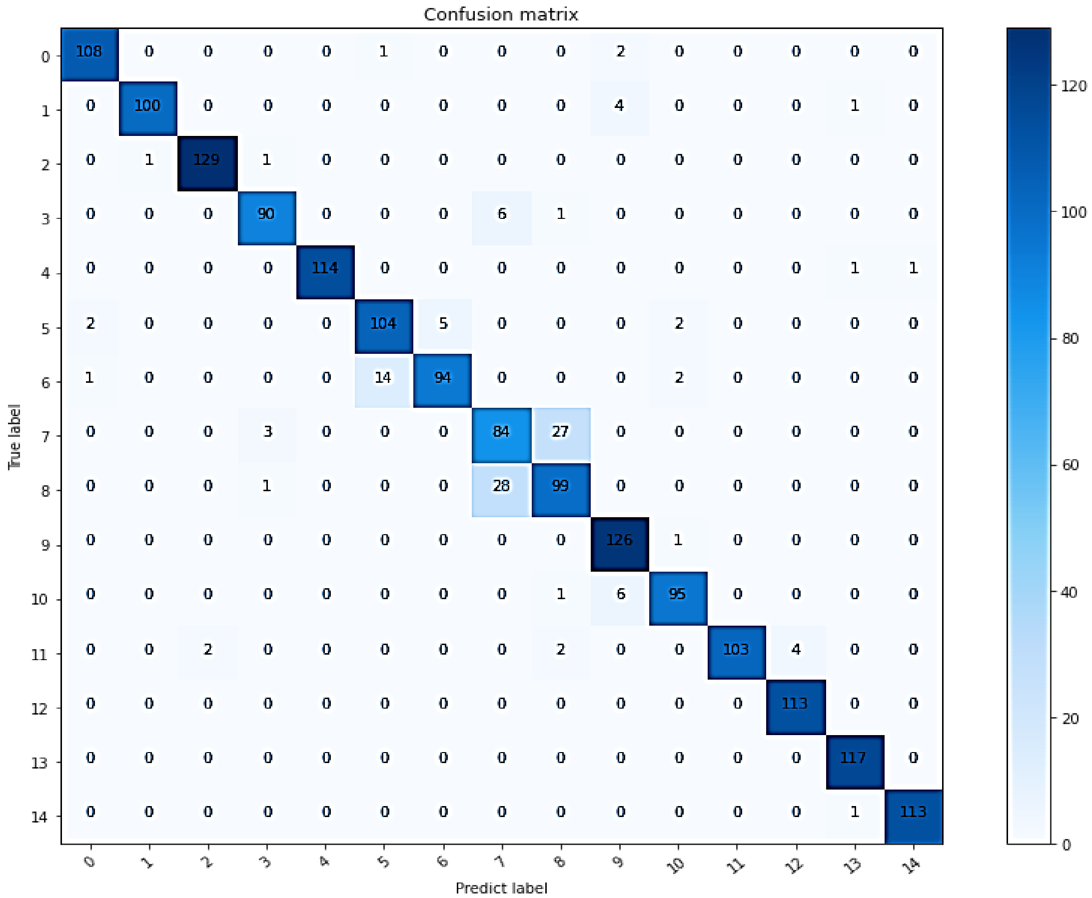


Figure 6.16 Confusion matrix for case study II

The training and testing accuracy increase as number of epochs increase, as shown in Figure 6.14 and it becomes constant after 1000 epochs as given in Figure 6.17. The maximum accuracy achieved by proposed model is 92.57%.

Table 6.4 Performance parameters of obtained for case study II

Fault label	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
0	97.30	97.30	97.30	99.65
1	99.01	95.24	97.09	99.65
2	98.47	98.47	98.47	99.77
3	94.74	92.78	93.75	99.30
4	100	98.28	99.13	99.88
5	87.39	92.04	89.66	98.60
6	94.95	84.68	89.52	98.71
7	71.19	73.68	72.41	96.26
8	76.15	77.34	76.74	96.49
9	91.30	99.21	95.09	99.24
10	95.00	93.14	94.06	99.30
11	100	92.79	96.26	99.53
12	96.58	100	98.26	99.77
13	97.50	100	98.73	99.82
14	99.12	99.12	99.12	99.88

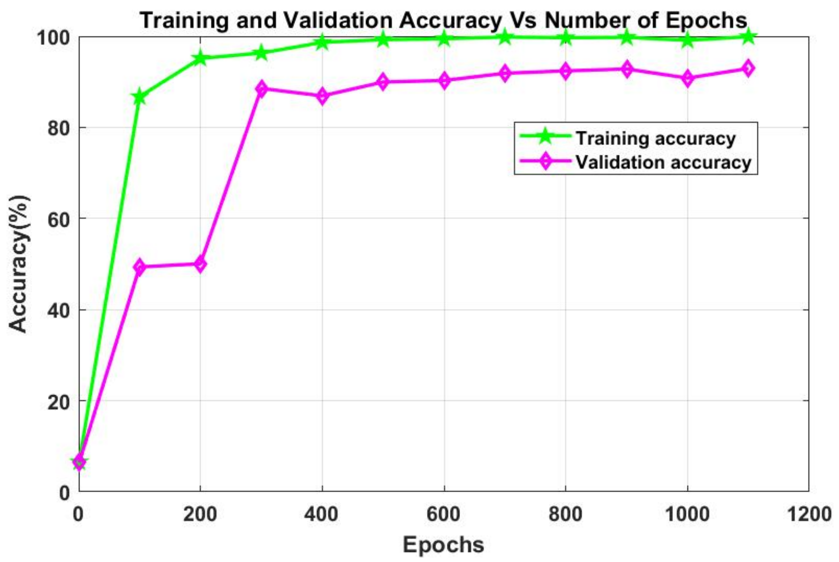


Figure 6.17 Training and testing accuracy over number of epochs

6.5 DEEP LEARNING MODEL USING CNN AND STACKED LSTM

In this part, the fault diagnostic model results on the experimental setup of an IC engine GB are discussed. Two datasets are observed from the experimental setup, one is bearing datasets and the other is gear datasets of the GB. Different performance parameters are evaluated on both datasets. The effect of different parameter selection on results is investigated, including filter length, number of filters and input size. Here, 11 trials of fault diagnosis model are considered to minimize randomness in the accuracy. All the experiments are performed on LENOVO PC with Intel Core i7 CPU, 8-GB RAM, Google Colab GPU and MATLAB R2018a.

6.5.1 Fault diagnosis architecture of model-II using CNN and LSTM

This model proposes multi-scale deep residual learning with a stacked long short-term memory (MDRL-SLSTM) fault classification model. The framework of proposed methodology is shown in Figure 6.18. This model comprises of feature extractors and feature classifiers, which takes raw vibration data as input into the deep learning model without any pre-processing techniques, like normalization. Two conditions of the gearbox are considered; healthy and defective state. The training and testing data is prepared from sampled signal and fed to deep learning model. Proposed model extracts feature automatically using CNN with residual learning and given to stacked LSTM for fault classification.

The categorical cross entropy loss function is adopted for minimizing error function using back propagation (BP) algorithm. BP algorithms are responsible for updating weights of neural networks layer. Categorical cross entropy loss function is used for multi-class classification as given equation (6.1). By using this loss function, it is easy to minimize error. BP algorithm is useful for updating the weights of NNs layer. Adam optimizer with a 0.0006 learning rate is adopted to train the network for 1000 epochs and a batch size of 128. After maximum epochs (i.e., finish training), testing samples are fed to fault diagnostic model for classification.

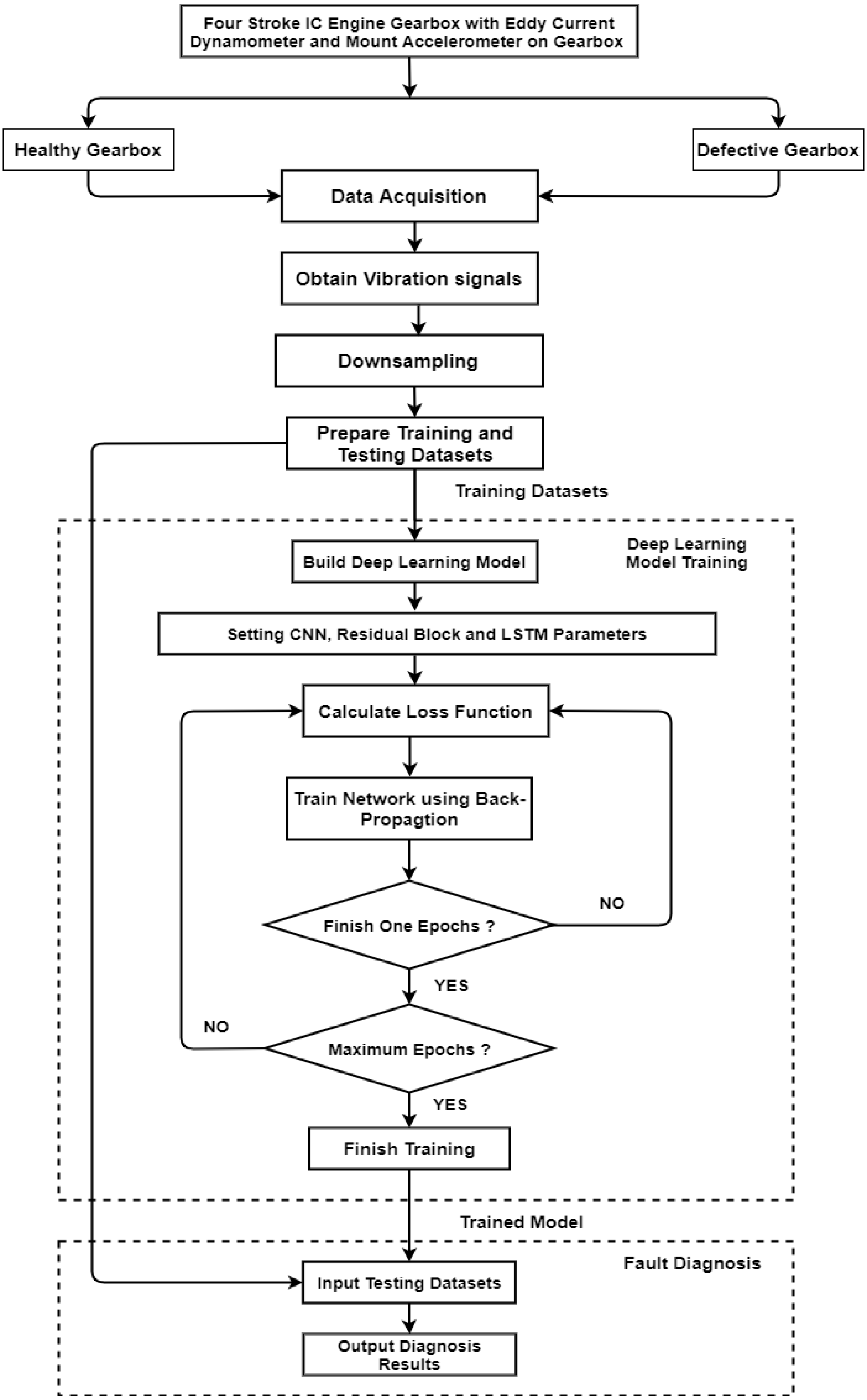
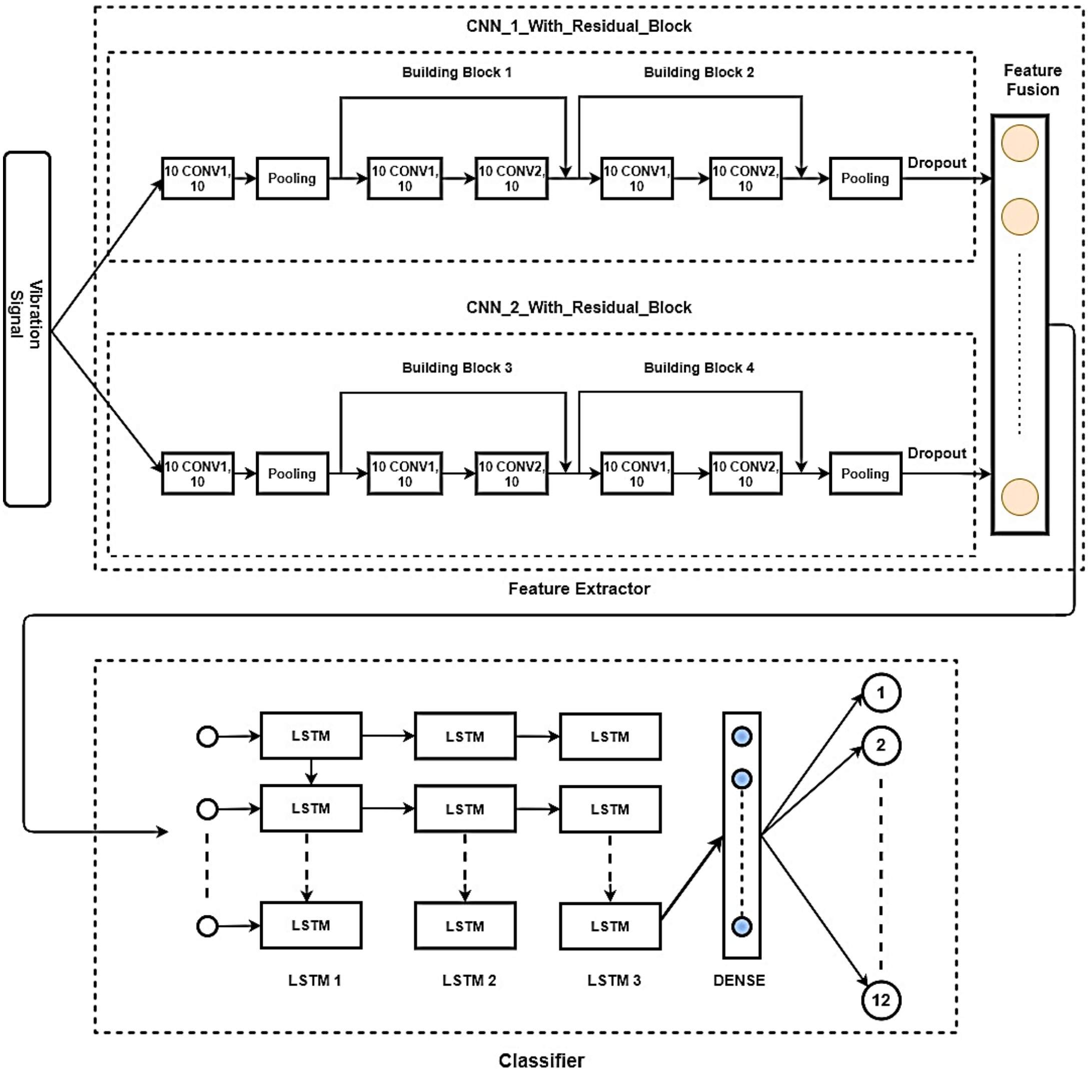


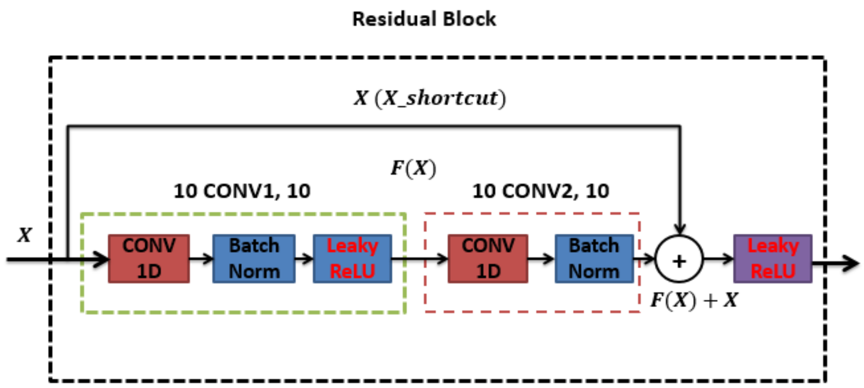
Figure 6.18 Proposed fault diagnosis flow chart based on deep learning model

This study proposes MDRL-SLSTM fault diagnosis model and allows vibration signal to be fed as input directly without any pre-processing like normalization, which nullifies the need of expertise on fault diagnosis and signal processing. The proposed deep learning model is inspired by the existing CNN-LSTM model with critical modification. Fault diagnosis model contains a feature extractor and classifier, as shown in Figure 6.19(a). Proposed architecture takes input raw vibration signal into feature extractor, which extracts high-level features using CNN with residual learning blocks based on vibration characteristics. The extracted feature is fed to stacked LSTM model for fault diagnostics-based on input feature. The raw vibration data is considered as input to the feature extractor module, which is comprised of two similar CNN with residual learning block (CNN_1_with_Residual_Block and CNN_2_with_Residual_Block) having the same dimensions. Each one having 1-D CNN and two residual block, illustration of residual block is given in Figure 6.19(b). The convolution block **10CONV1, 10** include 1-D convolution, BN followed by LeakyRelu activation function.

The 1-D convolution layer is the first layer with $F_N\,(10)$ filter kernel of window size $F_L\,(10)$ and convolution **10CONV2, 10** contains one convolution layer followed by BN. The BN is responsible for accelerating training process to achieve good accuracy and performance in a deep learning model. The LekyRelu activation function is adopted in proposed model to avoid gradient descent and diffusion problem. It is an extended function of Relu activation function with some more benefits. Residual block is designed with two weighted layers, each contains one convolution layer and BN layer. The output of residual block is given to pooling layer. Max pooling layer is used for extracting dominant features from previous feature vectors. The quality of pooling layer depends upon fault diagnosis problem and input datasets. Four residual blocks are used in feature extractor module with the same configuration. Feature vector from CNN_1_with_Residual_Block and CNN_2_with_Residual_Block are fused by element-wise product. These blocks provide several advantages like automatic feature extraction for different vibration signals and reduction in high dimension input data.



(a)



(b)

Figure 6.19 (a) The architecture of proposed MDRL-SLSTM model (b) Illustration of residual learning building block

The feature fusion layer's output is fed to feature extractor module, which contains three LSTM layer and one dense layer, each LSTM having different units. As shown in Figure 6.19(a), LSTM 1 provides hidden state to LSTM 2 and LSTM 2 output fed to LSTM 3. In the final state, output of 3rd LSTM layer is given to the dense layer for classification. Hence output of next layer is affected by output of previous layer. Dense layer contains softmax function which converts outputs into the probability distribution with different state of fault. The softmax function is defined by equation (6.15).

$$q(z_j) = softmax(z_j) = \frac{e^{z_j}}{\sum_{k=1}^{10} e^{z_k}} \tag{6.15}$$

where, z_j denotes output from jth neuron.

The proposed model can also perform well even with limited training datasets. Deep learning methods generally suffer from the heavy computational load. However, some deep learning tasks can be finished within few minutes, moreover, they can be run online as well as offline, hence the computational load of the proposed model is acceptable. Proposed deep learning framework has many advantages, such as: (i) compact model which takes raw vibration data as input; (ii) No preprocessing operation is required; (iii) Final trained deep learning model can be used to identify different fault conditions, etc.

6.5.2 Bearing fault diagnosis using multi-scale deep residual learning with a stacked long short-term memory (MDRL-SLSTM)

The case study I is done on bearing datasets of IC engine GB experimental setup. There are four-fault conditions considered; healthy, IR defect, OR defect and combined faults at IR and OR under three loading conditions i.e., no-load, load 1 and load 2 are considered for the analysis. In this study total of 12 different classes are considered for ball bearing, labelled as 0 to 11 as mentioned in Table 6.1.

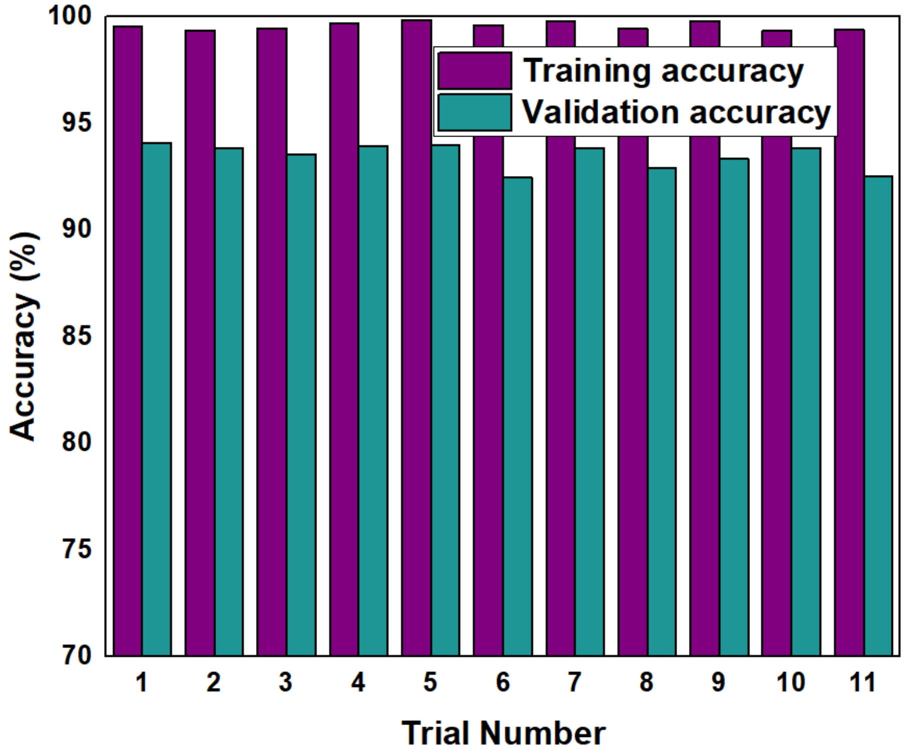


Figure 6.20 Accuracy of 11 trial

The raw data collected through the sensor contains a signal of 30 second duration and split into 30 samples with sampling rate of 25.6 kHz. Each condition includes 380 data samples (total 4,560 samples), each sample having 1000 data points. Input data is divided into 70% for training the model and 30% for testing. Therefore, 3192 data samples for training and 1368 samples for testing are used. The results of accuracy for 11 trials are shown in Figure 6.20. The proposed model gives training accuracy of more than 99% (near to 100%) and maximum validation accuracy up to 94.08%. Adam optimizer with 0.0006 learning is adopted to train the network for 1000 epochs with 128 batch sizes.

The performance parameters are calculated using the confusion matrix shown in Figure 6.21. It describes the classifier performance on the test data points. Performance parameters for each fault label are given in Table 6.5, lower accuracies are due to the misclassification in labels 3 to 4. Misclassification is due to some similarity between fault signals or presence of noise in vibration signal. Hence, if there is a noise in the faulty signal, classification becomes difficult.

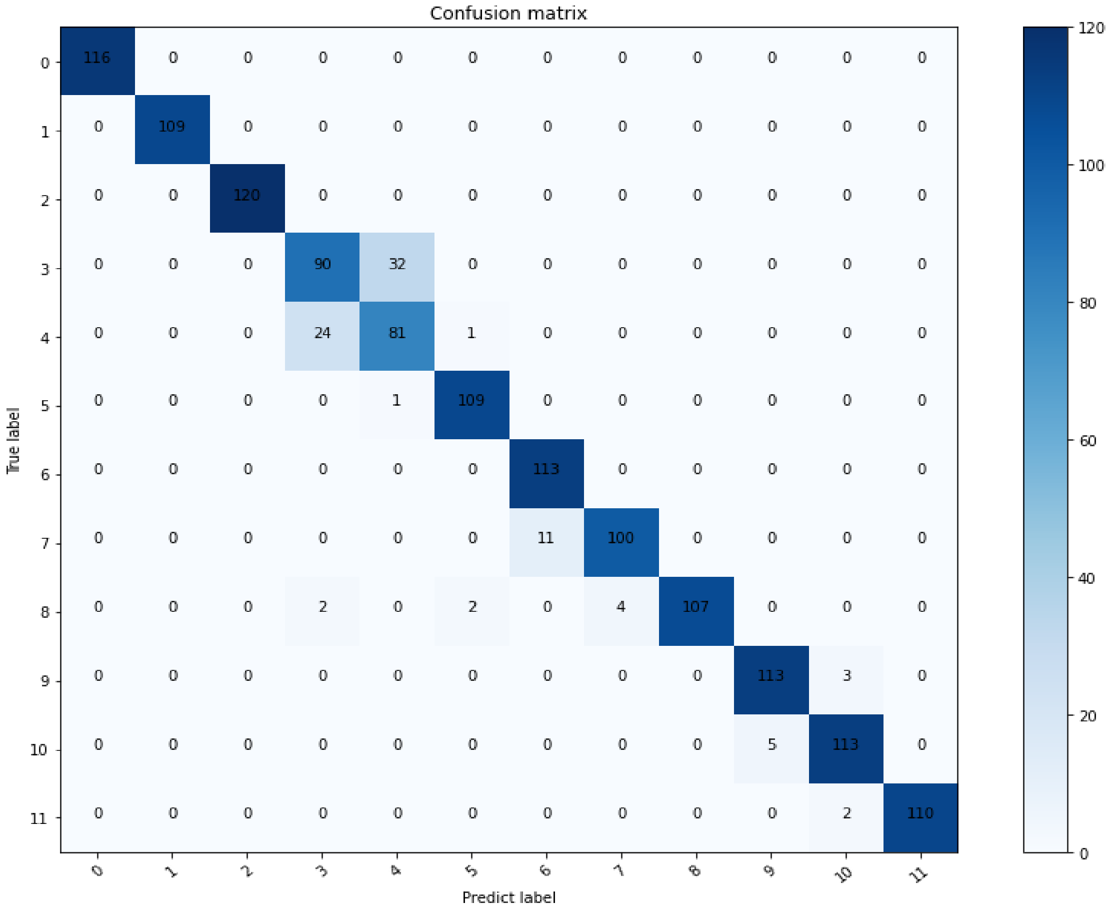


Figure 6.21 Confusion matrix for bearing classification

Training and validation accuracy increases as the number of epochs increases and becomes constant after some epochs, hence, less variation in training and validation accuracy.

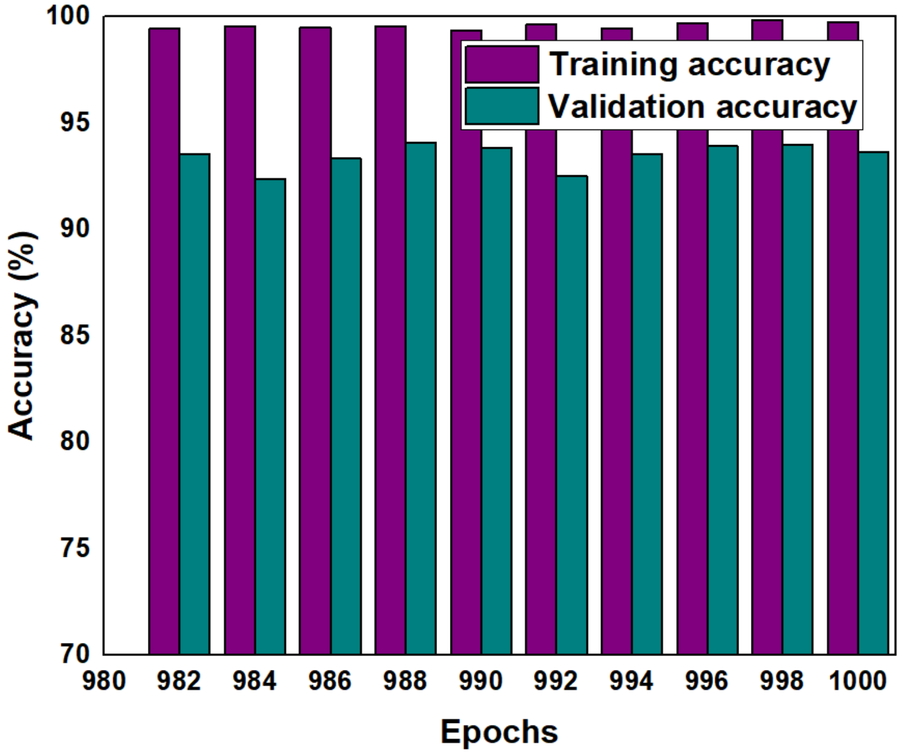


Figure 6.22 Accuracy after 900 epochs

Figure 6.22 shows the graph between accuracy and epochs. Both accuracies are constants after 900 epochs, as shown in Figure 6.23.

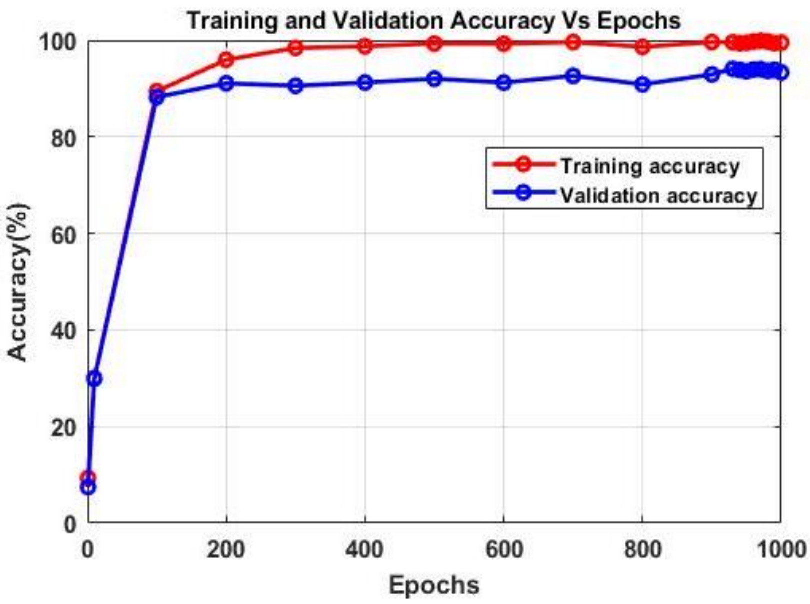


Figure 6.23 Accuracy vs epochs

Table 6.5 Performance parameters for case study I

Fault label	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
0	100	100	100	100
1	100	100	100	100
2	100	100	100	100
3	77.59	73.77	75.63	95.76
4	71.05	76.42	73.64	95.76
5	97.32	99.09	98.20	99.71
6	91.13	100	95.36	99.20
7	96.15	90.09	93.02	98.90
8	100	93.04	96.40	99.42
9	95.76	97.41	96.58	99.42
10	95.76	95.76	95.76	99.27
11	100	98.21	99.10	99.85

The maximum accuracy achieved by the proposed deep learning-based architecture is 94.08 %. Training and validation loss decreases as number of epochs increases and it is shown in Figure 6.24.

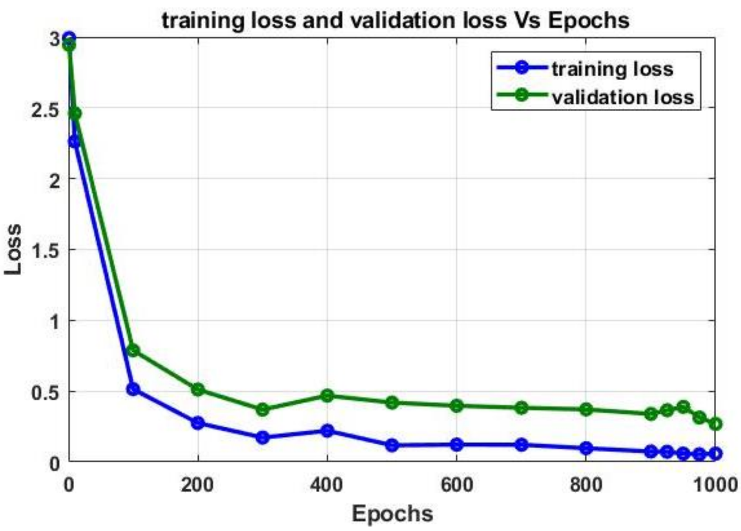


Figure 6.24 Loss vs epochs for bearing dataset

6.5.3 Gear fault diagnosis using multi-scale deep residual learning with a stacked long short-term memory (MDRL-SLSTM)

In case study II, healthy and progressive tooth defect conditions of gear data of GB are chosen for analysis. To make defect, tooth height is reduced by 1 mm for each condition and named as 25% defect, 50% defect, 75% defect and 100% defect, under three load conditions; no-load, load 1 and load 2 conditions. A total of 15 different classes of gear data are considered, labelled as 0, 1, 2 ...14, the details of which are given in Table 6.2. The model performance is evaluated for different conditions of gear and under different loading conditions. Each trial's raw data contains 25,600 data points and 30 iteration data for each class has been used. Similar to the bearing data (in case study I), investigations have been done with gear data. For each fault, 380 data samples are taken and each sample contains 1000 data points. 70% of the input data, 3990 samples, is used for training and the remaining 30%, 1710 samples, is used for testing.

Based on vibration characteristics of gear data, proposed model automatically extracts deep features from the data, with no requirement of manual interference. These features are given to the classifier for fault classification. Adam optimizer with 0.0006 learning rate is adopted for training the model for 1000 epochs with 128 batch size.

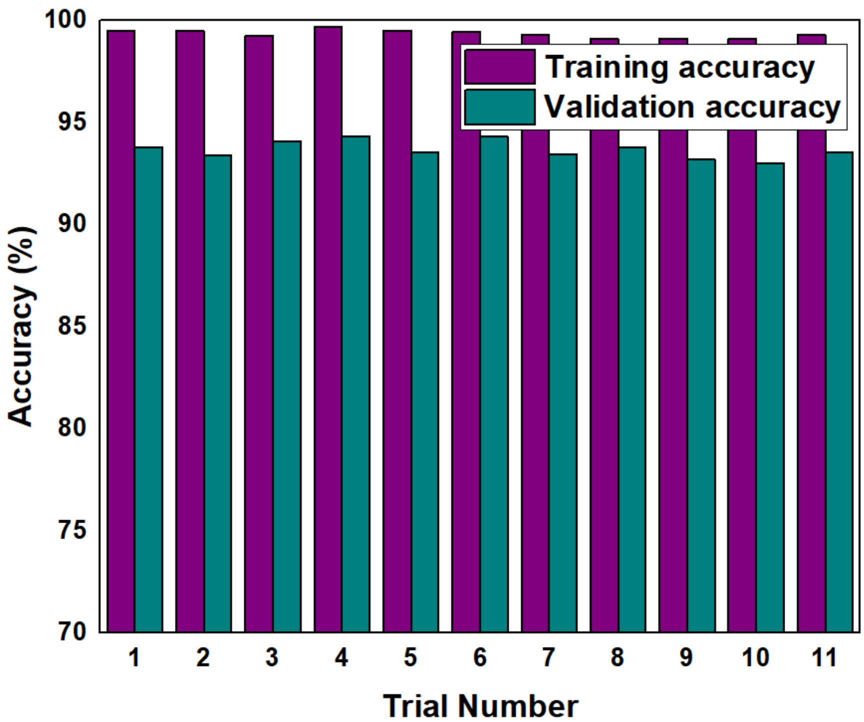


Figure 6.25 Accuracy vs number of trials

Figure 6.25 shows the accuracy in terms of number of trials. Results show that maximum training accuracy achieves more than 99% (near to 100%) and maximum validation accuracy is 94.33%.

Table 6.6 Performance parameters for case study II

Fault label	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**Accuracy (%)**
0	99.19	98.39	98.79	99.82
1	99.14	94.26	96.64	99.53
2	95.24	100	97.56	99.65
3	83.94	95.83	89.49	98.42
4	91.87	100	95.76	99.42
5	79.10	94.64	86.13	98.01
6	94.44	74.56	833.33	98.01
7	91.67	56.90	70.21	96.73
8	77.21	95.45	85.37	97.89
9	91.89	93.58	92.73	99.06
10	92.79	99.04	95.81	99.47
11	99.07	96.36	97.70	99.71
12	100	99.01	99.50	99.94
13	100	93.28	96.52	99.53
14	100	97.41	98.69	99.82

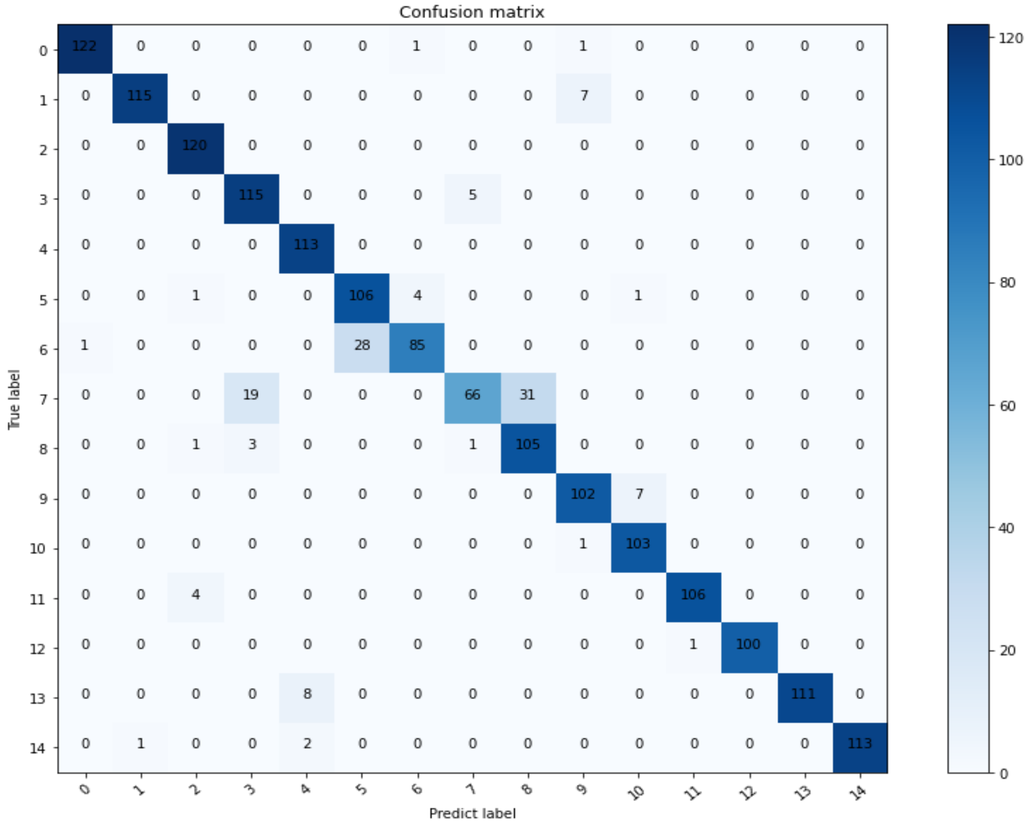


Figure 6.26 Confusion matrix for gear classification

Performance parameters are also tabulated, like precision, F1-score, Accuracy and Recall are given in Table 6.6. Lower accuracy is the reason for misclassification in labels 4, 6, 8 and 9. The confusion matrix is used for calculating the performance parameters, as shown in Figure 6.26.

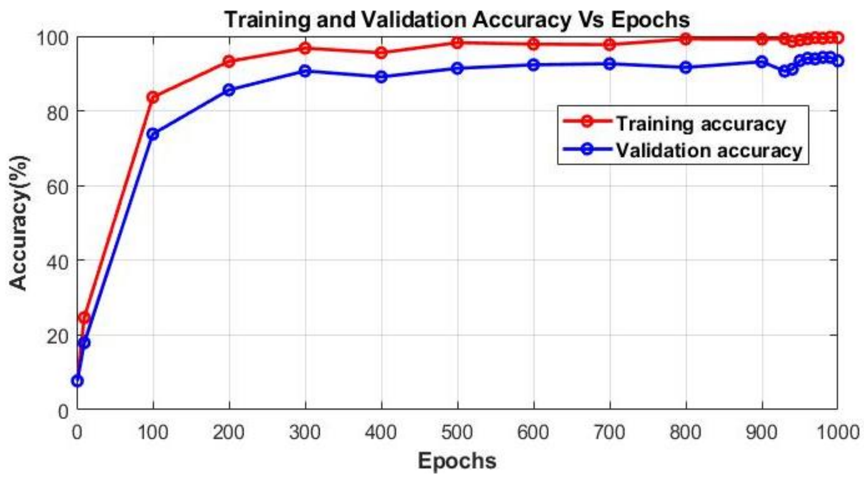


Figure 6.27 Training and validation accuracy over number of epochs

The training and validation accuracy increases with epochs and becomes constant after 900 epochs, as shown in Figure 6.27, hence, there are variations in the accuracy.

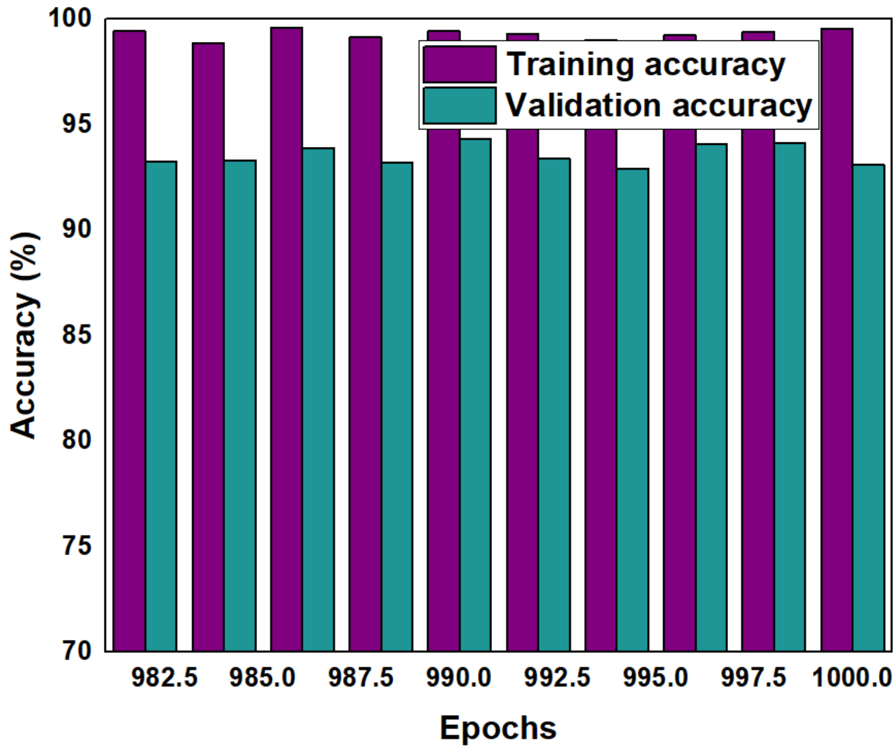


Figure 6.28 Accuracy after 900 epochs

In Figure 6.28, the bar graph shows, that after 900 epochs and it indicates constant accuracy after 900 epochs. Training and validation loss decreases as number of epochs increases and it is shown in Figure 6.29.

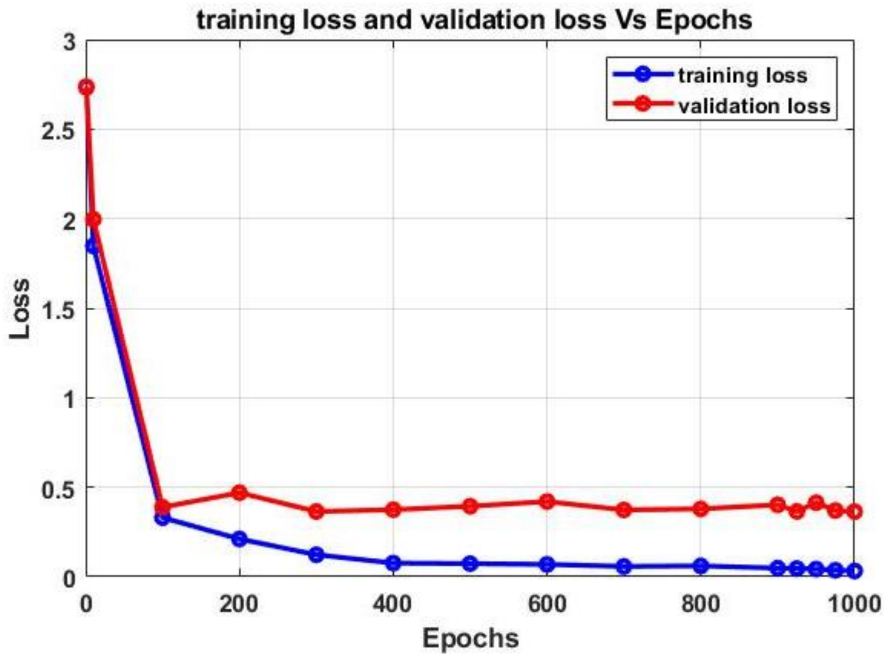


Figure 6.29 Loss vs epochs for gear dataset

6.6 SUMMARY

This chapter gives the detailed applications of deep learning techniques in fault diagnosis of bearing and gear. CNN with residual learning is used for extracting features from the vibration signals of the gearbox. Softmax and LSTM methods were used for classification of faults based on the extracted features. The results obtained from both model-I and model-II proves efficiency of deep learning model for automatic feature extraction and classification of gearbox elements. Thus, the proposed methodology with deep learning techniques can be recommended for practical applications and development of on-line fault diagnosis systems for IC engine gearbox condition monitoring using vibration analysis.

CHAPTER 7

SUMMARY AND CONCLUSIONS

7.1 SUMMARY

Experiments were conducted on two stroke and four stroke IC engine gearbox. Vibration signals were acquired for healthy and faulty conditions of the gearbox. Fault diagnosis was performed using signal processing, ML and DL techniques. In the following sections brief summary of two stroke and four stroke engine analysis is discussed.

7.1.1 Fault diagnosis of ball bearing in two stroke IC engine gearbox

Fault investigation of ball bearing is one of the significant research areas in condition monitoring of IC engine gearbox. In this study, signal processing techniques such as time domain analysis, spectrum analysis and CWT analysis were used for fault diagnosis of ball bearing using vibration signals.

Experiments were conducted on output shaft ball bearing with healthy and faulty conditions of the gearbox. Vibration signals of IC engine were acquired and used to identify the faulty conditions in the ball bearing. Machine learning techniques were also employed for online condition monitoring of IC engine gearbox. Statistical, EMD and DWT features were extracted from the recorded vibration signals. Decision tree was used for selecting most contributing features for classification. Artificial intelligent models such as SVM, random forest algorithm and K star models were used as classifiers for classifying the conditions of the bearing.

7.1.2 Fault diagnosis of ball bearing in four stroke IC engine gearbox

This study is about monitoring ball bearing used in the four stroke IC engine gearbox using condition monitoring techniques. Experiments were conducted on four stroke IC engine gearbox which was connected to Eddy current dynamometer for applying external load. Vibration signals were acquired from the gearbox with triaxial accelerometer. Ball bearing with healthy and induced faulty (outer race fault, inner race fault, inner and outer race fault) conditions were used in the analysis. Fault diagnosis of the ball bearing were carried out using machine learning and deep learning techniques. For all the conditions of bearing, statistical, EMD and DWT features were extracted from the vibration signals. Decision tree technique (J48 algorithm) was used in the analysis for selecting significant features from the feature vector. From the chosen features, ball-bearing conditions were classified using SVM, random forest algorithm and K star algorithm. Results obtained from the different classifiers were compared and a best classification algorithm with a decision tree were suggested for condition monitoring of the rotating components. Also, deep learning methods such as CNN with residual learning, softmax function and LSTM were used for fault diagnosis of the bearing.

7.1.3 Fault diagnosis of gear in four stroke IC engine gearbox

The purpose of the study was to diagnose faults in second driving gear in gearbox of an IC engine using vibration signals with signal processing, machine learning and deep learning techniques. Experiments were conducted on real-time running condition of IC engine gearbox while considering combustion. Vibration signals from the gearbox were acquired for healthy and induced faulty conditions of the gear. In the study, 25% tooth fault, 50% tooth fault, 75% tooth fault and 100% tooth fault were chosen as the condition of the driver gear. The acquired signals were processed and analysed using signal processing and machine learning techniques. Spectrum, cepstrum, short-time Fourier transform (STFT) and wavelet analysis were performed. Spectrum, cepstrum and CWT provided better information about gear fault conditions using time–frequency characteristics. The obtained results show the variation in the amplitude of the crankshaft rotational frequency (CRF) and gear mesh frequency (GMF) for different conditions of the gearbox with various load conditions. Machine learning techniques were also employed in developing the fault diagnosis system using statistical, EMD and DWT features. The performance of deep learning techniques was discussed in implementing automatic feature extraction from the raw vibration signals and classification is performed using softmax and LSTM methods. K-star algorithm with J48 decision tree provides better classification accuracy of about

96% in identifying gearbox conditions for DWT features. The proposed approach can be used effectively for fault diagnosis of IC engine gearbox.

7.2 CONCLUSIONS

Following were the conclusions drawn from the study on fault diagnosis of two stroke and four stroke IC engine gearbox using vibration analysis through signal processing, ML and DL techniques.

7.2.1 Ball bearing fault diagnosis in two stroke IC engine

Following were the conclusions drawn from the study on fault diagnosis of bearing in two stroke IC engine gearbox using signal processing and ML techniques.

- Results have shown that the spectrum analysis and CWT analysis were very effective in identifying the conditions of ball bearing. CWT plots have provided the information about ball bearing condition in the range of frequency band 500–1500 Hz with the variation of amplitude corresponding to different fault conditions. Hence, it is suggested to use CWT technique in the applications of fault detection of ball bearing in IC engine.
- From this investigation of bearing fault, SVM algorithm provided a classification accuracy of about 96% with statistical features and 97.33% with DWT features.
- K star and random forest algorithms were able to attain classification accuracy of about 98% with statistical features.
- K star achieved classification accuracy of 99.33% in association with DWT features and decision tree algorithm. This is highest among all other combinations of features and classifiers.
- Experimental results show that data mining techniques like decision tree combined with random forest algorithm and K star model for classifying faults in machinery gives good classification accuracy. Based on the results, K star and random forest algorithm can be suggested for the diagnosis of faults in two stroke IC engine ball bearing using DWT features.

7.2.2 Ball bearing fault diagnosis in four stroke IC engine

Following were the conclusions drawn from the study on fault diagnosis of bearing in four stroke IC engine gearbox using ML and DL techniques.

- The fault classification accuracy was evaluated using statistical, EMD, DWT feature extraction techniques with classifiers such as SVM, random forest and K star for bearing. It was found that K star classifier with DWT feature yielded better accuracy than rest of the classifiers with classification accuracy 91.94 % in case of bearing diagnosis. Use of DWT features with all three classifiers resulted in better classification accuracy. Hence, it is recommended for classification instead of statistical features and EMD features.
- CNN with residual learning is able to get acceptable diagnostic performance with limited vibration data for training the model. Proposed model achieved 93.79% diagnostic accuracy for bearing of an IC engine gearbox.
- CNN with multi-scale deep residual learning with a stacked long short-term memory (MDRL-SLSTM) model was proposed for fault classification. It resulted in diagnostic performance with 1-D vibration data of GB and classification accuracy of 94.08% is achieved on bearing datasets.

7.2.3 Gear fault diagnosis in four stroke IC engine

Following were the conclusions drawn from the study on fault diagnosis of gear conditions in four stroke IC engine gearbox using signal processing, ML and DL techniques.

- Time domain analysis shows dynamic variation in amplitude with change in gear (Healthy, 50% defect and 100% defect) and loading conditions, which can be noticed with increased value of RMS during the analysis.
- Spectrum plots depict harmonics of CRF and GMF with increase in amplitude for different conditions of the gearbox faults.
- Cepstrum plots provided quefrency of GMF and also gave information regarding amplitude variation with respect to different conditions of the gearbox.

- STFT provided better frequency information, but did not give clear evidence about time variation with respect to frequency. The gear mesh frequency band of 1000 Hz - 1300 Hz can be seen in STFT plots for different conditions of gear.
- CWT spectrograms gave time–frequency information with respect to amplitude variation for different conditions of the gearbox. In the spectrogram, harmonics were clearly visible in the frequency band of 800 Hz - 1500 Hz.
- The fault classification accuracy was evaluated using statistical, EMD, DWT feature extraction techniques with classifiers such as SVM, random forest and K star for bearing.
- K star model has resulted in a maximum classification accuracy of about 95.77% with DWT features as compared to other classifiers with any feature's extraction techniques listed.
- The combination of random forest model with DWT feature technique has provided a good classification accuracy of about 94%, which is nearer to the highest classification accuracy 95.77% (obtained by the K star model with the DWT features).
- CNN with residual learning was able to get acceptable diagnostic performance with limited vibration data for training the model. Proposed model achieved 92.57% accuracy for gear data set of an IC engine gearbox.
- CNN using multi-scale deep residual learning with a stacked long short-term memory (MDRL-SLSTM) model was proposed for fault classification. Proposed model achieved good diagnostic performance with 1-D vibration data of GB and classification accuracy of 94.33% was attained on driving gear data.

7.3 CONTRIBUTIONS

This main contribution of the present study are;

- Bearing and driver gear of four stroke IC engine and also, bearing of two stroke IC engine were diagnosed for their frequent failure modes through vibration signal by employing signal processing, machine learning and deep learning.
- An attempt has been made to explore the new machine learning algorithms such as K-star algorithm, random forest to classify various gearbox conditions.

- It is vital in ML to select algorithm which results in good classification accuracy. Hence a comparative study of ML techniques was carried out.
- To overcome the problem associated with ML, deep learning was employed where, the manual feature extraction and need of preprocessing raw data was eliminated.
- Automatic feature extraction methods using convolutional neural network and residual learning are explored to analyze raw vibration signals from the gearbox to classify the health conditions of bearing and gear.

7.4 SCOPE OF FUTURE WORK

- Hardware based monitoring system can be designed and implemented for multiple gearboxes located at remote locations.
- Real time condition monitoring of gearbox using other signals such as sound, acoustic emission, temperature, combustion pressure etc. can be considered for diagnosing the conditions.
- IC engine components like piston, crankshaft, cylinder liner and other elements can be monitored using machine learning and deep learning techniques.

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APPENDIX I

1. **Four Stroke IC Engine**

Make: Bajaj Discover 125 ST

Engine parameter	**Particulars**
Type of engine	DTS-I, 4-stroke, natural air cooled
Number of cylinders	1
Torque	10.8 Nm @ 5500 rpm
Displacement	124.6 cc
Power	11 bhp @8000 rpm
Number of gears	Five speed constant mesh gearbox
Final drive ratio	3.214:1

2. Eddy Current Dynamometer

Make: SAJ India Pvt Ltd, Pune

Dynamometer Parameter	Particulars
Model	ED 1
RPM	1500-3000
Torque	7.5 KW
Type	Eddy current
Serial Number	234/166
Year of Manufacture	2012-13

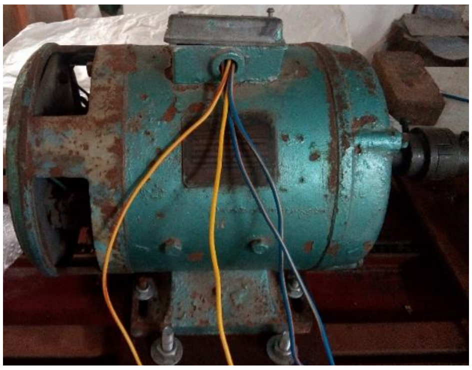
3. Two Stroke IC Engine

Make: Kawasaki KB-100/100RTZ

Engine Parameter	Particulars
Type	Two stroke, air cooled
Number of cylinders	1
Bore	49.5 mm
Stroke	51.8mm
Volume	99.69cm^3
Compression ratio	11:1
Max net power	10.10 HP at 7500 RPM
Max net torque	1.09 kgf.m at 7000 RPM
Transmission	4 Speed gearbox
Final drive ratio	3.385:1

4. DC Motor

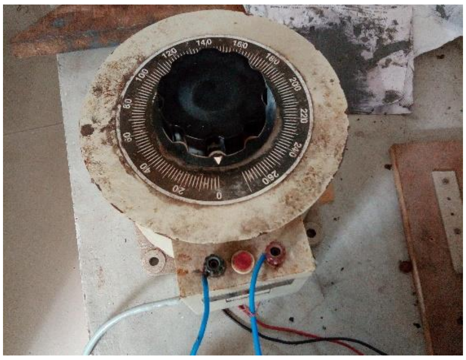
Make: Khalsa Foundry and Workshop, Kanpur



Parameter	**Specification**
Rated Power	3 hp
Rated Voltage	230 V DC
Max Current	12 A
Max speed	1440 rpm

5. Dimmerstat

Make : Ravistat



Parameter	**Specification**
Rated Input voltage	230 V AC
Output Voltage range	0 – 260 V AC
Max Load	12.21 kVA
Max Current	15 A

6. Tri axial Accelerometer

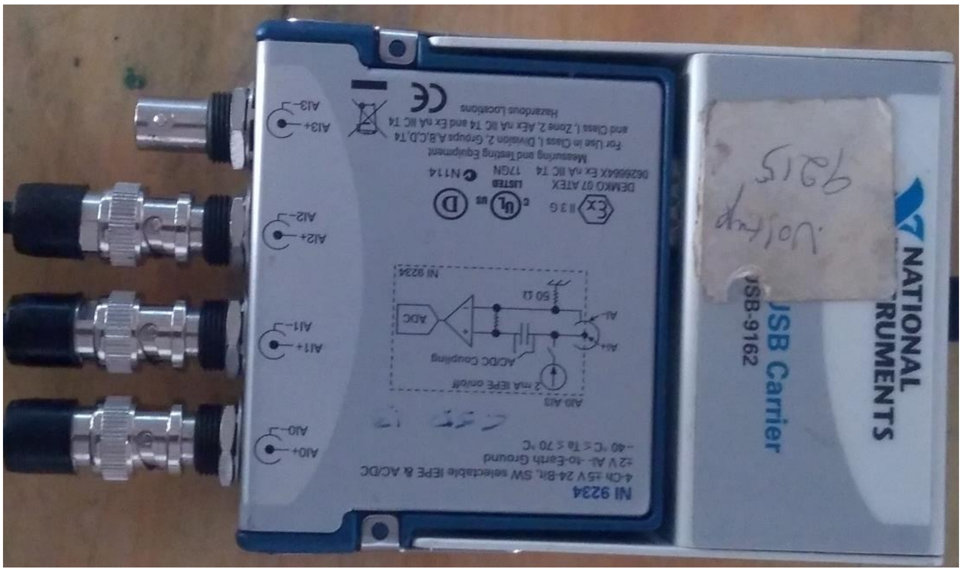
Make: YMC Piezotronics China

Model	YMC145A100
Sensitivity X	97.9 mV/g
Sensitivity Y	95.65 mV/g
Sensitivity Z	104.6 mV/g
Measuring range	±50
Temperature range	-41 to 121 ˚C
Case Material	Stainless steel
Size	25.4 ∗ 25.4 ∗14 mm

7. Data Acquisition System

Make: National Instruments

Model	NI 9234
Voltage	±5 V, AC/DC analog input
Sampling rate	51.2 kS/s/ch
Channel	4 channel module
Temperature range	-40 to 70 ˚C


NI 9234

LIST OF PUBLICATIONS

INTERNATIONAL JOURNALS

1) **K.N. Ravikumar**, C.K. Madhusudana, Hemantha Kumarand K V Gangadharan., (2021) "Classification of Gear Faults in IC Engine Gearbox using Discrete Wavelet Feature and K-star algorithm" **Journal:** *Engineering Science and Technology, an International Journal* (JEST-EC), Elsevier Publishing, **(SCIE and SCOPUS Indexed, IF-4.36, Q1 Journal)**, https://doi.org/10.1016/j.jestch.2021.08.005
2) **K.N. Ravikumar,** Akhilesh Yadav, Hemantha Kumar, K.V. Gangadharan, A.V. Narasimhadhan., (2021) "Gearbox Fault Diagnosis based on Multi-Scale Deep Residual Learning and Stacked LSTM Model", **Journal:** *Measurements-Journal of the International Measurement Confederation (IMEKO)*, Elsevier Publishing, **(SCIE and SCOPUS Indexed, IF-3.927, Q1 journal),** https://doi.org/10.1016/j.measurement.2021.110099
3) **Ravikumar K.N.,** Hemantha Kumar., Kumar G. N.and K.V. Gangadharan., (2020) "Fault Diagnosis of Internal Combustion Engine Gearbox using Vibration Signals based on Signal Processing Techniques" **Journal:** *Journal of Quality in Maintenance Engineering, Emerald Publishers*. **(SCOPUS and ESCI Indexed, Q2 Journal)** https://doi.org/10.1108/JQME-11-2019-0109
4) **Ravikumar K.N.,** Suhas S. Aralikatti., Hemantha Kumar., Kumar G N.and K V Gangadharan., (2021) "Fault diagnosis of antifriction bearing in internal combustion engine gearbox using data mining techniques" **Journal:** *International Journal of System Assurance Engineering and Management, Springer Publishing.* **(SCOPUS and ESCI Indexed, Q3 Journal),** https://doi.org/10.1007/s13198-021-01407-1
5) **Ravikumar K.N.,** Hemantha Kumar., Kumar G N.and K V Gangadharan., (2019) "Fault Diagnosis of IC Engine Gearbox Using Statistical Features of Vibration Signals Through Random Forest Algorithm" **Journal:** *Structural Durability and Health Monitoring*, Tech Science Press Publishing. **(SCOPUS Indexed, Accepted for publication, Q3 Journal)**

CONFERENCE PROCEDDEINGS

1) **K.N. Ravikumar**, Hemantha Kumar and K.V. Gangadharan., (2019, December) “Application of Vibration Analysis and Data Mining Techniques for Bearing Fault Diagnosis in Two-Stroke IC Engine Gearbox”, Second International conference on Design, Materialsand Manufacture (ICDEM-2019), NITK-Surathkal, India, 6-8 December 2019. Published in AIP Conference Proceedings 2247, 020016 (2020), **(SCOPUS Indexed)**; https://doi.org/10.1063/5.0003811
2) **K. N., Ravikumar,** Hemantha Kumar and Gangadharan, K. V., (2018, December). “Condition Monitoring of Two Stroke IC Engine Ball Bearing Based on Vibration Signals Using Machine Learning Techniques” An International Conference on Tribology (TRIBOINDIA-2018), VJTI-Mumbai, India, 13-15 December 2018. Published in proceedings of TRIBOINDIA-2018 An International Conference on Tribology, Available at SSRN: https://ssrn.com/abstract=3313485 or http://dx.doi.org/10.2139/ssrn.3313485
3) **Ravikumar K.N.,** Madhusudana C.K., Kumar H., Gangadharan K.V. (2017, December) “Ball Bearing Fault Diagnosis Based on Vibration Signals of Two Stroke IC Engine Using Continuous Wavelet Transform” 13th International conference on vibration problems (ICOVP-2017), IIT Guwahati, India, November 29 – December 2, 2017. Published in Springer Book Titled “Advances in Rotor Dynamics, Controland Structural Health Monitoring. Lecture Notes in Mechanical Engineering”. Springer Publisher, **(SCOPUS Indexed);** https://doi.org/10.1007/978-981-15-5693-7_28.
4) **Ravikumar K.N.,** Hemantha Kumar and K.V. Gangadharan., (2017, December) “Condition Monitoring of Ball Bearing Based on Vibration Signals of Two Stroke IC engine using Decision Tree and K-Star algorithm”, National symposium on Rotor Dynamics (NSRD-2017), IIT-Patna, India, 12-13 December 2017.

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M.Tech in Design Engineering	KLECET, Belagavi	2013	76.92%
B.E in Mechanical Engineering	TCE, Gadag	2011	62.40%

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Srinivasa Institute of Technology, Mangalore	Assistant Professor	2013	2015

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Conference Publications : 4

I declare that above information is true and correct to best of my knowledge and belief.

(Ravikumar K.N.)