Deep Learning based Model for Design and Fault Diagnosis for Ball Bearing

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By

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CERTIFICATE

This is to certify that the Research work titled "**Deep Learning based Model for Design and Fault Diagnosis for Ball Bearing"** that is being submitted by **Pragya Sharma** is in partial fulfillment of the requirements for the award of **Master of Technology**, is a record of bonafide work done under my guidance. The contents of this research work, in full or in parts, have neither been taken from any other source nor have been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

Bearings are very important elements in all small hand-held to large heavy-duty rotating machinery. Any bearing with a fault can lead to an unexpected machine failure which results in economic loss, long downtimes, etc. Early detection of the fault of the ball bearing is very important to avoid failure of the machine system and to avoid any kind of accident due to machine failure. This work is for developing a deep learning-based model for design and diagnosis of fault embedded in a ball bearing. To overcome the disadvantages of traditional methods for identification and diagnosis for ball bearing fault, the method of 1-D Convolutional Neural Network (1-D CNN) is used. 1D CNN is developed for fault identification and then fault classification which are embedded in any of the race of bearing. The adaptive design of 1-D CNN model presents an ability to fuse extraction of features and classification of fault in a single learning body. 1- D arrays are used in this model which leads towards less computational complexity. 1-D CNN is very useful technique to identify real-time problem due to its low computational complexity requirement. This method can be implemented for diagnosis of the faults in ball bearing either it exists on any race. For the advantage of higher accuracy, this approach can be implemented for real-time condition monitoring of bearing. Open-source data "Society for Machinery Failure Prevention Technology (MFPT fault dataset for bearing)" is used in this work for training and testing purposes. The main focus for using the 1-D CNN approach is to get higher accuracy in fault diagnosis and less computational complexity for results.

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List of Abbreviations

1.	ML	Machine Learning
2.	DL	Deep Learning
3.	ANN	Artificial Neural Network
4.	CWRU	Case Western Reserve University
5.	MFPT	Society for Machinery Failure Prevention Technology
6.	FFT	Fast Fourier Transform
7.	STFT	Short Term Fourier Transform
8.	EA	Envelope Analysis
9.	WT	Wavelet Transform
10.	PCA	Principal Component Analysis
11.	SVM	Support Vector Machine
12.	MLP	Multi-Layer Perceptron
13.	BPFI	Ball Pass Frequency of Inner Race
14.	BPFO	Ball Pass Frequency of Outer Race

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Chapter – 1

Introduction

1.1 Project background and motivation

Bearings are widely important machine elements in all small hand-held to large heavy-duty rotating machinery. In ball bearings, the separation between moving parts is maintained by rolling elements. The main function of any bearing is to reduce friction between moving parts. Bearing is an important machine element that is responsible for effortless functioning in rotating machines [1]. Any bearing with a fault can lead to an unexpected machine failure which results in economic loss, long downtimes, etc. As any fault in the bearing can reduce the life of rotary machines and failure of rotary machinery will be a reason for costly downtimes and also for any accidental activity in the workspace, so it is very important to identify the bearing fault embedded on the races. The defects on any bearing can be categorized in two ways, either localize or distributed defects. The distributed defect is extended completely across the raceway but localized defects are not completely distributed in the raceway. The diagnosis of bearing fault is very important to reduce the cost and downtime. Fault diagnosis is a very important process of condition monitoring of any mechanical component and machine system. The benefits of this early detection of fault are enhancement in safety and reduction in maintenance cost. Early detection of the fault of the ball bearing is very important to avoid failure of the machine system and to avoid any kind of accident due to machine failure.

1.1.1 History of ball bearing

The very first device which was based on a ball-bearing element was discovered in the Roman Empire about 40AD. In that device, there was a rotating table and the balls are below that rotating table. By using that table, people eating at that table simply rotate the table to serve the food easily. The next design for a ball bearing used in a rotary device or machine was found after 1500 years was found by Leonardo. Later on, almost after 100 years Galileo also mentioned a ball bearing design. Until 1791 there was no patent field and design for a ball bearing. and then the first patent on ball bearing was given to Philip Vaughan in 1971.

In ancient times when the wheel was not created at the start of human civilization, the concept of bearing had already used. Figure 1 shows a rolling vehicle which was used to carry heavy weight by dragging the vehicle. In this vehicle, the rolling logs were placed beneath heavy objects which makes the dragging of heavy loads easier. Different kinds of liquids were used as lubricants for smooth functioning [2,3].

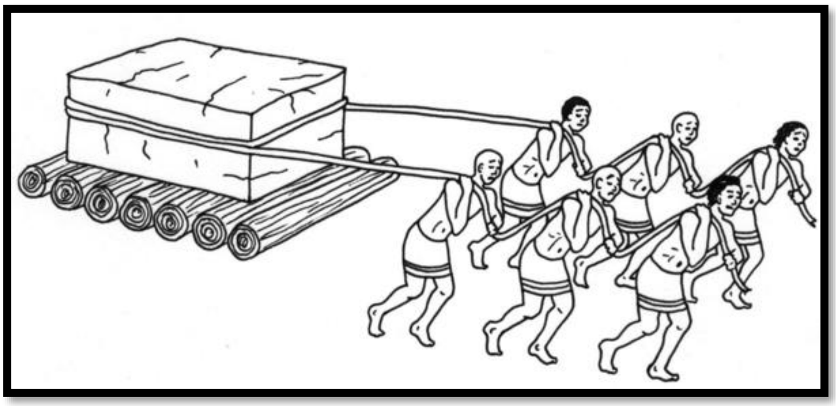

Figure 1: The concept of roller bearings used to move heavy stone pieces [3].

1.1.2 The Industrial Age

In the industrial age, the ball bearing was invented with different designs and materials. Invention of Leonardo da Vinci between 1498-1500 is shown in figure 2. The design of ball bearing was focused to reduce the friction between moving plates. This bearing was used in the famous design of helicopter [4]. Leonardo da Vinci used wooden material to make ball bearing but at early of industrial age due to the growing advancement in metal forming processes, steel was used as ball-bearing material because steel bearings were far better than wood bearings. Philip Vaughan was awarded with a patent for his modern ball bearing design in 1794. This bearing reduces a large amount of friction which was the main requirement for an efficient machine.

Figure 2: Ball bearing design invented by Leonardo da Vinci [4]

1.1.3 Present Day

In 1869, Jules Suriray designed the radial ball bearing which was also awarded for patent and that bearing was used in bicycles. This improved design was a success and led to the research and development of new different varieties of metal ball bearings. Sven Winquist gave a new bearing design which was a self-aligning design. During the 20th century, the research continued to change and improve the bearings. The requirement for all mechanical systems is bearings which could support forces and combined loads applied axially and radially in the system and reduces a large amount of friction to get an efficient machine system

In a ball bearing, balls are the rolling element which is used to separate the races of bearing. The main function of a ball bearing is the reduction in friction in rotational direction and to provide support at the loads. As the failure of ball bearing can lead towards machine breakdown, costly downtimes, the condition monitoring of the system is very important which is used to identify the faulty bearing in the system. Figure 3 shows a healthy and defective bearing.

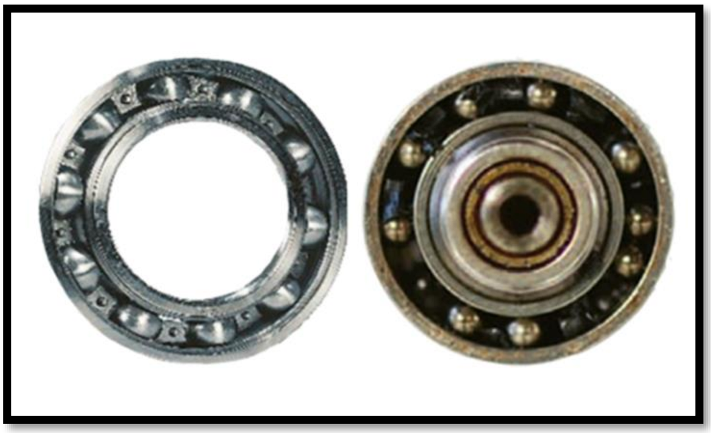

Figure 3: Healthy and defective Ball Bearing

1.2 Aim and Objective

Conventionally, to diagnose the fault embedded in any race or ball of ball bearing, different methods were employed for the extraction of features and then classification. The accuracy of traditional methods was very low due to the requirement of manual expertise. The major problem when large data is used for fault diagnosis for bearing by using existing techniques is that the manual features extraction requires prior and advance knowledge of techniques used for signal processing and expertise is also required for the diagnosis. The models of shallow structure or architecture which are used in traditional methods of bearing fault diagnosis limits the capability of system in diagnosis of fault [5,6]. From the last three years, all attention is provided to variants of deep learning approaches for machine fault diagnosis and this approach can be used for both steps of extraction of features by using vibration data and fault classification also. A technique of deep learning method which is 1-D CNN is used in this work for identification and classification of faults embedded in the outer race of the bearing. If any fault exists in ball bearing, the vibration spectrum deviates with some degree from their vibration spectrum of health condition. This vibration data is used for feature extraction and then classifiers are used for fault classification. 1-D CNN is used in this work for feature extraction as well as fault classification.

In literature, there are significant applications of deep learning approaches in fault diagnosis [6,7]. But the main requirement for applying these techniques is a big labeled dataset for training and testing purposes. Computational complexity is also very high for these approaches. To overcome these drawbacks, the advanced approach of CNN, 1-D

CNN is recommended which is less complex in computation as 1-D data is processed in CNN layers.

The main objective of the dissertation work is the development of a deep learning-based model for design and diagnosis for a ball bearing fault. In this work, we will be modeling the ball bearing with the help of mathematical equations used in the literature. We will be using open source data “Society for Machinery Failure Prevention Technology (MFPT bearing fault dataset)” for modeling and analysis purposes. We will be using a machine learning/ deep learning-based approach using MATLAB programming.

Chapter – 2

Literature Review

2.1 Reviews

This paper mainly focuses on the techniques which are based on vibration analysis used for the detection of fault embedded in bearing. several vibration techniques which can be used for detection of bearing fault like Fast Fourier Transform (FFT), Short Term Fourier Transform (STFT), Envelope Analysis (EA), Wavelet Transform (WT), etc. were reviewed in the paper to identify and explore their capabilities, advantages, and disadvantages of these techniques for bearing fault detection. Vibration data forbearing for testing purposes was taken from Case Western Reserve University (CWRU) Bearing Data Centre. Vibration data was analyzed for four conditions: normal state, inner race fault, outer race fault, and ball fault. A comparative study of FFT, STFT, EA, WT techniques for fault diagnosis of bearing were presented in this paper. Bearing fault identification is very difficult by using frequency analysis because this analysis technique could not be used for non-stationary signals due to instability of results. The major drawback of envelope analysis is the requirement of preliminary research of the resonance frequencies to analyze and identify the defect. The problem in using STFT for fault identification is that it gives a constant resolution for all frequencies as this technique uses the same level and same window for the entire signal [8].

This paper summarizes existing study on the diagnosis of bearing fault using machine learning (ML) and data mining techniques is presented. By analyzing the drawbacks of machine learning techniques like artificial neural network (ANN), principal component analysis (PCA), support vector machines (SVM), etc., they mentioned the advantages of the use of deep learning (DL) techniques for bearing fault diagnosis. The first focus is to provide conventional ML methods review and then it gives the advantages of the use of DL algorithms for analysis of faults embedded in ball bearing instead of conventional ML techniques. Also, to get more deep knowledge, a review-based study is mentioned in this paper for getting classification accuracy of different algorithms utilizing the different open-source datasets. The different datasets mentioned in this paper are Case Western Reserve University (CWRU) bearing dataset, Paderborn University dataset, PRONOSTIA dataset, and Intelligent Maintenance Systems (IMS) datasets for comparative study. Whether a large dataset is required for training of DL algorithms, they can automatically perform adaptive feature extraction for bearing fault diagnosis without any prior expertise on characteristic frequencies of bearing fault [9].

In this paper, the author discussed about frequency features of a bearing extracted from vibrational data required for motor bearing fault diagnosis. The author presented an approach of neural networks and time and frequency domain bearing vibration analysis for fault diagnosis. Neural networks are implemented to diagnose the fault of motor rolling bearing and then the vibration frequency feature of bearing and time-domain characteristics are implemented with the neural network to construct an automatic bearing fault detection machine. Figure 4(a) and (b) show the signal flow in the conventional fault detection process and neural network-based fault detection process in the motor bearing. At the beginning of the training session of the neural network, it does not give accurate results. An error quantity is quantified and measured and then it was used to adjust the internal parameters of the neural network to get more accurate output. Both vibration simulation and actual experimental results are discussed to validate the accuracy and drawbacks of the neural network used for bearing vibration diagnosis algorithm for bearing fault detection using vibration data [10].

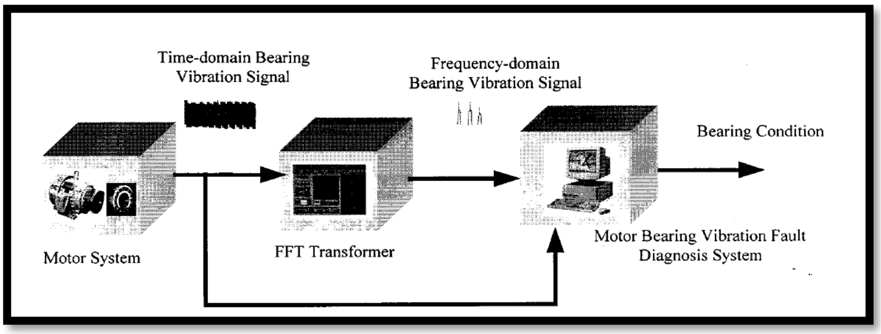

Figure 4(a): signal flow in a conventional fault detection process in motor bearing [10]

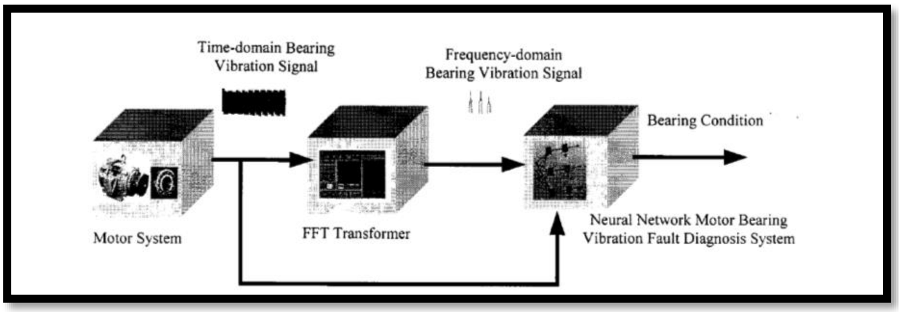

Figure 4(b): signal flow in Neural network-based fault detection process in motor bearing [10]

This paper discussed the Condition-based monitoring (CBM) methodology utilized for the diagnosis of bearing faults. The vibration-based analysis is a very accurate technique of condition-based monitoring to identify the actual condition on machine and machine components. In this paper, the author mentioned the conventional convolutional neural network (CNN) used for pattern recognition and analysis. The author used CNN as a back-end classifier for fault detection of the ball bearing. Vibration data is used for three different bearing condition. The first condition is of healthy bearing, second condition is when the fault is embedded at the inner race and the third condition is when the fault is embedded at the outer race. The extraction of statistical features of bearing from vibration data is done separately and then forwarded into CNN classifier as an input for further fault classification. The accuracy and precision are then compared with other studies to analyse the reliability and efficiency of the technique used for bearing fault diagnosis [11].

As the technique of Convolutional Neural Nets (CNN) is widely used in image processing. The author of this paper applied CNN algorithms to image and acoustic data analysis. In this paper, the pre-processing of the initial vibration signal is avoided. Pre-processing is done to remove the noise of the vibration signal and also for the extraction of features by using vibration signal and data. The author avoided the pre-processing and directly raw vibration signal is applied to convolutional neural nets. This paper explored the CNN approach for the classification of different types of signals of vibration by using various rolling element bearing datasets. Bearing dataset of Case Western Reserve University is used to analyse and compare the accuracy of this approach. This paper shows that the convolutional filters trained by CNN help to get more classification accuracy. But the conventional CNN algorithm is not able to process 1D vibration signal data [12].

In this paper vibration-based analysis of bearing fault is done by using convolutional neural network algorithms. The author described and used manually extracted features like inner and outer race ball pass frequencies, spin frequency of bearing balls, kurtosis, crest value for fault detection. All the features used are manually extracted which require human expertise for feature extraction which is a major drawback for this testing and analysis technique. Further the author proposes a feature learning model for condition-based monitoring based on CNN. The motive of this approach is to automatically detect the features used for fault detection. The analysis is done for fault at the outer and inner race, healthy bearing, degradation due to lubrication in bearing, and also for fault due to rotor imbalance. For each category of fault, several bearings are used to test and then ensure the generalization in the fault detection system. Furthermore, this approach of automatic feature learning is compared with other feature engineering-based approaches by using the same data for comparing the performance of approaches. The results in this paper indicate that the feature-learning approach which is based on convolutional neural networks is better than the classical feature-engineering based approach which uses manually engineered features and a random forest classifier. The former achieves an accuracy of 93.61 percent and the latter an accuracy of 87.25 percent [6].

The author represented the Convolutional Neural Networks (CNNs) technique used for bearing fault detection. As CNN has become the *de facto* standard for various Computer Vision and Machine Learning operations, the advantages of this approach are mentioned in this paper. Deep 2D CNNs architecture having a large number of hidden layers and millions of parameters is used in this paper. This deep 2D CNN architecture can learn complex objects and signal patterns by training of network on a massive size visual database and a large dataset is required for training purposes. By training the 2D CNN algorithms, this approach can analyze 2D signals such as images and video frames. But the main drawback of this 2D CNN approach that it is not able to analyze the 1D signal especially for the training of the algorithm [13].

Bearings are one of the most critical components of power drives and rotary machines. The author of this paper discussed the effective diagnosis approaches of bearing faults. In this advanced technological world, there is a massive collection of real-time data and when the conventional existing methods are used for bearing fault diagnosis with such large data, these techniques are not able to give accurate results. When these existing methods are used, the features from bearing data are to be extracted manually which requires advanced knowledge and expertise about techniques of signal processing and these techniques are also not able to process very large data. For the pre-processing of signals, the author used Short Term Fourier Transform (STFT) to obtain a simple spectrum matrix and then an optimized deep learning approach, Large Memory Storage Retrieval (LAMSTAR) neural network is applied for fault diagnosis of bearing. Acoustic emission signals were acquired from the test rig and these signals are then used to validate the approach used in this work. The performance is also compared with other methods of bearing fault diagnosis mentioned in the literature. This approach is better than conventional techniques but it is not able to process 1D vibration signals and separate pre-processing of the signal is required in the approach mentioned in this paper [14].

Chapter – 3

Problem description

The main objective of dissertation work is to develop a deep learning-based model for design and fault diagnosis for a ball bearing. in this work, effective deep learning algorithms for bearing fault detection are developed, and for that algorithm a large collection of bearing datasets is required. We will be using open source data "Society for Machinery Failure Prevention Technology (bearing fault dataset)" for modeling and analysis purposes.

The ball bearing itself act as a vibration source even if the bearing is in healthy condition and there is no fault in bearing and they are perfectly installed, aligned, and adjusted. The fault present at bearing increases the level of vibration signal of bearing. There are several types of defects like cracks, pits, wear, etc. that can be at any location like inner race, outer race, and rolling elements of bearing. If the rolling element hits the location where the fault is present at the raceways, the level of vibration increases at that location in every rotation of the rolling element. These distributed or localized defects present in ball bearing can be detected by a transducer from the vibration data and then analyzed and processed with the network algorithm. Figure 5 shows an example of the change in vibration patterns due to the presence of a fault in a ball bearing.

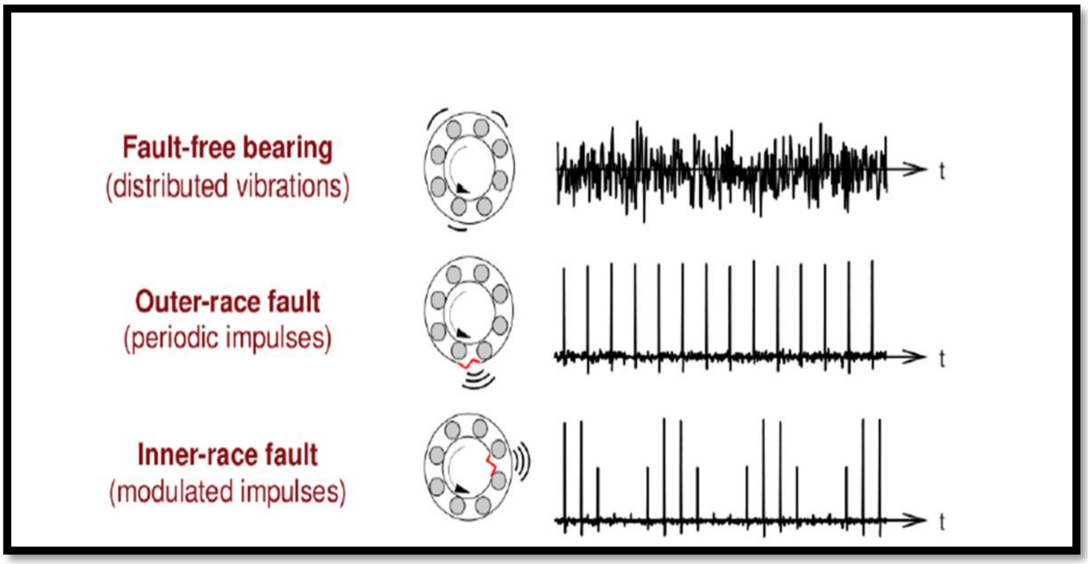

Figure 5: Ball bearing defects and their vibration pattern. [15]

Whenever the rolling element of ball bearing hits or makes contact with the defect on any of the races, the impulse is created by this strike. This impulse is created periodically with a certain frequency as with every rotation of rolling element of bearing. in case the fault is at the inner race, the frequency of striking the fault by rolling element is termed as ball pass inner race frequency and determined by the geometry of bearing and rotation speed. Similarly, when the fault is at the outer race, the striking frequency is called a ball pass outer race frequency. These frequencies can also be computed theoretically and the formulation is given in the next chapter.

In this work we will obtain the spectrum of feature frequencies of rotating machines under different health conditions. Then raw data is pre-processed with a time and frequency domain transformations using algorithms. Then we will Import the obtained frequency spectra into deep learning-based algorithms. On the basis of requirement and application, various types of deep learning approaches can be used. Then we will employ the optimized deep learning model to diagnose the bearing faults. Then achieved signals from the test rig will be compared and analyzed by using the Deep Learning method (1D CNN) with the vibration data available by MFPT bearing datasets to identify the defect location and the size on the rolling element bearing.

Chapter – 4

Ball Bearing Geometry and Defects

4.1 The Geometry of ball bearing

Bearings are widely important machine elements in all small hand-held to large heavy-duty rotating machinery. In ball bearings, the separation between moving parts is maintained by rolling elements. The main function of any bearing is to reduce friction between moving parts. Bearing is an important machine element that is responsible for effortless functioning in rotating machines. Various types of ball bearings are thrust ball bearing, axial ball bearing, angular contact ball bearing, deep groove ball bearings, etc.

The main components of a ball bearing are shown in figure 6 are a cage, inner and outer ring, and rolling element or balls. The cage can also be called as the separator. The rolling element or balls make contact with the hard surface of the inner ring and outer ring. The area of the inner and outer ring which makes the contact with the balls are called the inner race and outer race respectively. The geometrical quantities which play a very important role in a ball bearing geometry are pitch diameter, rolling element diameter, and the number of rolling elements in the bearing. Figure 7 shows the load zone for a ball bearing which is associated with the load applied to the center of the inner ring in a horizontal direction. Whenever the external load is applied to the bearing rolling elements may lose their contact with inner or outer race or with both the races and then the system becomes highly nonlinear system [16]. Where the balls are still in contact with any of the race and load is also carried by bearing, that contact area is referred to as the loaded zone of the bearing. Externally applied axial loading and preloading at the bearing provide uniformly distributed contact loads in the bearing. the load distribution profile depends on the geometry of bearing and also on the direction of the applied load.

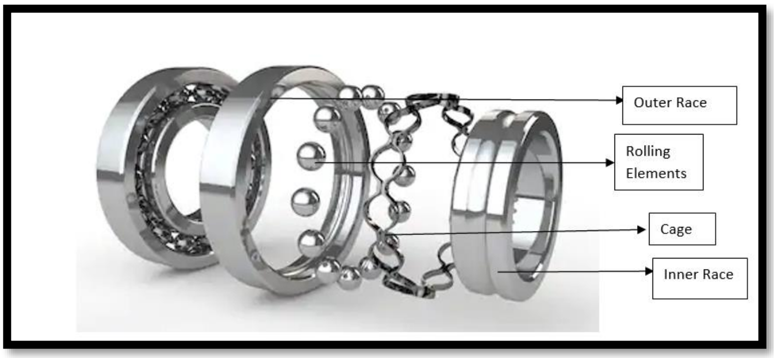

Figure 6: Ball bearing and its components

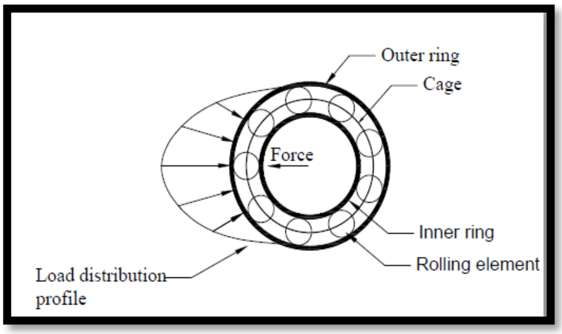

Figure 7: Schematic view of a rolling element bearing and its components.

For a rolling element bearing, the most important geometrical parameters are pitch diameter, rolling element diameter, width, bore diameter, and the number of rolling elements. These mentioned important geometrical parameters are shown in figure 8.

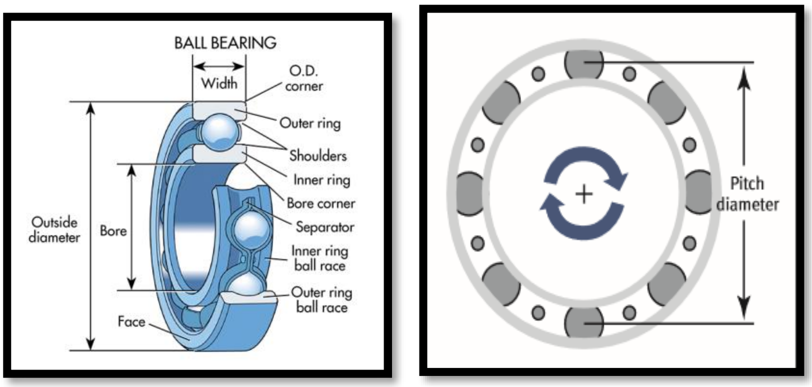

Figure 8: Important geometrical parameters of ball Bearing

4.2 Bearing Defect Types

Any fault in the bearing can reduce the life of rotary machines and failure of rotary machinery will be a reason for costly downtimes. Failure of bearing can cause personal injury or accident at the workplace and unscheduled repair or replacement of rotating machines which lead toward high maintenance cost. Rolling element bearings may become defective at different stages through the service life of the bearing for several reasons. At the early stage of the bearing service life, the problem with the design of bearing can lead towards a defective bearing. Defects can also be a result of manufacturing errors, overloads, misalignment, and wrong installation. Bearing defects are described into two categories: localized and distributed defects. Distributed defect covers the entire surface of bearing races such as surface roughness, waviness, different size rolling elements which are due to manufacturing errors. The localized defects are not like distributed defects, they did not cover the entire surface of the raceway and focused on one position. Wear, crack, fatigue are examples of the localized defect. This type of fault may arise due to insufficient lubrication between the contact surfaces. Faults in the bearing can be a result of improper installation, lubrication, maintenance, improper handling practices. The fault or defects of bearing can also be divided into the following categories:

3.2.1 Wear Damage

Wear on the bearing races is a very common defect that occurs by dirt sitting on the area and other particles entering through polluted lubrication oil and inadequate sealing. Wear damage results in increased friction between moving profiles. This wear damage gradually deteriorates the bearing.

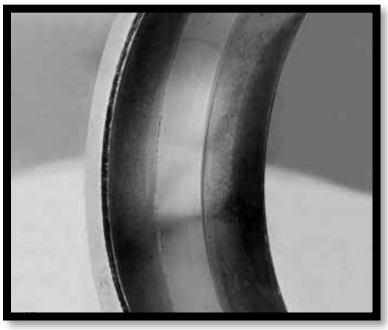

Figure 9: Outer ring of the bearing is worm by abrasive particle [17]

3.2.2 Fatigue Damage

Just after running the bearing for some time, the loaded bearing fails and the reason is material fatigue. Also, if a bearing is at overstressed or preloaded condition, after a span of service time, it stops working because of fatigue damage. Starting point of fatigue crack in the material is lower part and the crack travels on the surface as loading continues. It will continue until metal breaks because of this fatigue crack. Over loading and over speeding are the reason for fast growing of fatigue crack.

3.2.3 Corrosion Damage

The excessive noise during the operation is caused by rust pits occurred by the corrosion on the elements of bearing. If the surfaces of bearing are presented to water, oil containing acid, corrosive, and improper storage, the rust is created. Condensation is also a reason of corrosion. It occurs by the immediate change in temperature from the different operating temperatures of bearing in the air.

Figure 10: Roller bearing defect due to corrosion [17]

3.2.4 Overheating

Different symptoms are discoloration of balls, rings, and cages from Black/Blue gold to blue. Temperature to the excess of 400°F can anneal the ball and ring materials. The result of this is the reduction of hardness which reduces the working capacity of bearing and early failure occurs. The worst condition is the deformation of balls and rings due to overheating. The rise in temperature can also destroy or degrade lubricant.

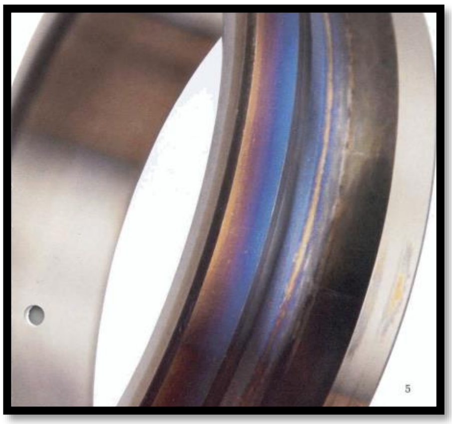

Figure 11: Roller bearing defect due to overheating [17]

3.2.5 Brinelling

When the rolling element is overloaded, it generates permanent indentation. This is called Brinelling. Static load is the reason for indentation; this can lead towards plastic deformation of the raceways. The same defect can also occur when a bearing is opened to shock loads and vibration. This defect is obvious on the races caused by the indentations or wear and this defect increase the noise and vibration in the bearing, which can lead to early bearing failure.

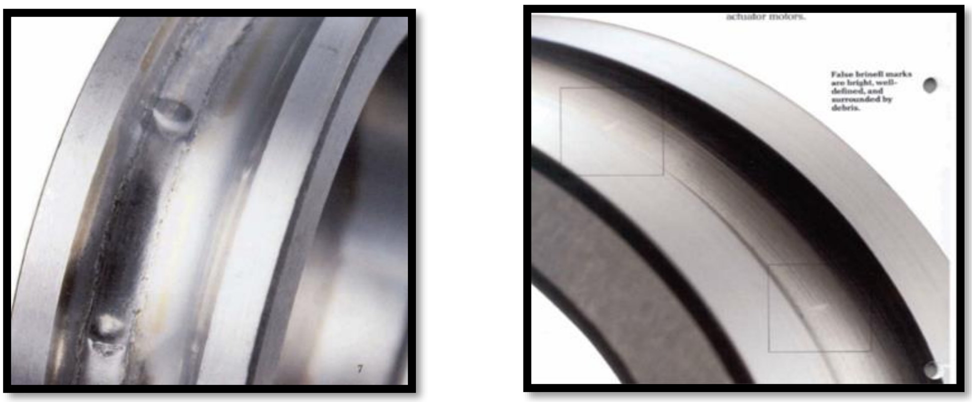

Figure 12: defects due to brinelling [17]

3.2.6 Shaft Misalignment

The misalignment of the shaft is another common cause of the bearing failure. It wears mostly the outer race and in case of a high misalignment, it causes an unusual temperature rise which can result in other types of faults. These defects are typically distributed defects in the load zone.

3.2.7 Excessive Load

The immoderate permanent load can generate premature fatigue which will usually appear similar to the normal fatigue. In this scenario, the bearing does not have the proper capacity to cope up with the applied load. So, for this the greater capacity bearing should be used or the load should be reduced.

Chapter 5

Statistical parameters and Dataset for bearing fault diagnosis

5.1 Statistical parameters for feature extraction

In the earlier work, these different features were extracted manually or by any other method in which high expertise was required, and then a different method was used for the classification of the fault in a ball bearing. But nowadays, with this advanced approach of CNN based on deep learning, features are extracted automatically, and then the required feature for further analysis is adaptively selected by the model itself based on the effectiveness and importance of the feature. In table 1, we have presented different features extracted in the literature.

Table 1. Statistical parameters for feature extraction [18]

Feature	**definition**
1. Mean Value	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
2. Root Mean Square (RMS)	$RMS = \left[\frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)\right]^{1/2}$
3. Standard Deviation	$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$
4. Kurtosis Value	$KV = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{\sigma}\right)^4$

5. Crest Factor	$CF = \dfrac{max(\lvert x_i \rvert)}{\left[\frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)\right]^{1/2}}$
6. Inner Race Ball Pass Frequency	$BPFI = f_s \dfrac{N}{2}\left(1 + \dfrac{D_B}{D_P} cos\alpha\right)$
7. Outer Race Ball Pass Frequency	$BPFI = f_s \dfrac{N}{2}\left(1 - \dfrac{D_B}{D_P} cos\alpha\right)$
8. Ball Spin Frequency	$BSF = f_s \dfrac{N}{2D_B}\left(1 - \dfrac{D_B^2}{D_P^2} cos\alpha\right)$
9. Cage frequency or Fundamental Train Frequency	$FTF = \dfrac{N}{2}\left(1 - \dfrac{D_B}{D_P} cos\alpha\right)$

Where,

x - Vibration signal

n - Number of sampling points

f_s – Shaft Speed

N – Number of balls

D_B – Ball diameter

D_P – Pitch diameter

α – Contact angle between the inner race and outer race

5.2 MFPT dataset

Machinery Failure Prevention Technology (MFPT) data set [19] is an open-source data for ball bearing fault diagnosis. For the MFPT dataset, the have used a type of NICE bearing in the test rig.

Parameters of bearing

Diameter of ball	0.235
Pitch Diameter	1.245
Number of balls	8
Contact angle	0

Dataset of MFPT is categorized into three sections of bearing vibration data which are baseline condition, inner race fault condition, outer race fault conditions. For the baseline set of data, 3 files are sampled with the sample rate is 97656 Hz for 6 sec per file. For the outer race fault condition dataset, 7 files are sampled with the sample rate is 48828 Hz for 6 sec per file. And for the inner race fault condition dataset, 7 files are sampled with the sample rate is 48828 Hz for 3 sec per file. All the data in the data were obtained at different load conditions.

Chapter 6

Methodology

6.1 2D CNN – A brief introduction

There is a neural-biological model of animal visual cortices [20] by which the convolutional neural network is biologically motivated and CNN is a deep learning algorithm base on Artificial Neural Network. At first convolution process is used to image processing and image recognition hierarchically like first, it used for simple features as edge and corner, and then it is used for extracting complex features. There are three main stages in the convolution operation in which two stages are for filtering and the other stage is for classification. In the architecture or the structure of 2-D CNN (figure 13) two layers exist, one is a convolutional layer and the other one is the pooling layer. To get deep in the network this combination of convolutional and pooling layer is repeated in the model. The convolutional and pooling layer is the filter stage of the model. The input in the process is a 2-D image of ball bearing with the fault of any type. The convolutional layer generates a new feature map image from the raw input image. The feature map image includes unique features of the input image by processing the 2-D data. This layer contains filters that are called as convolution filters. The other filtering stage is of pooling layer which lowers the size of the output image of convolution filters. Then the output of these two-filtering stages which is the hidden layers of the model is transferred to the third stage of fully connected layers and then the output is forwrded in the best classifier to get the detail if the fault is present in the ball bearing. These classifiers are based on SoftMax or Sigmoid functions [21,22].

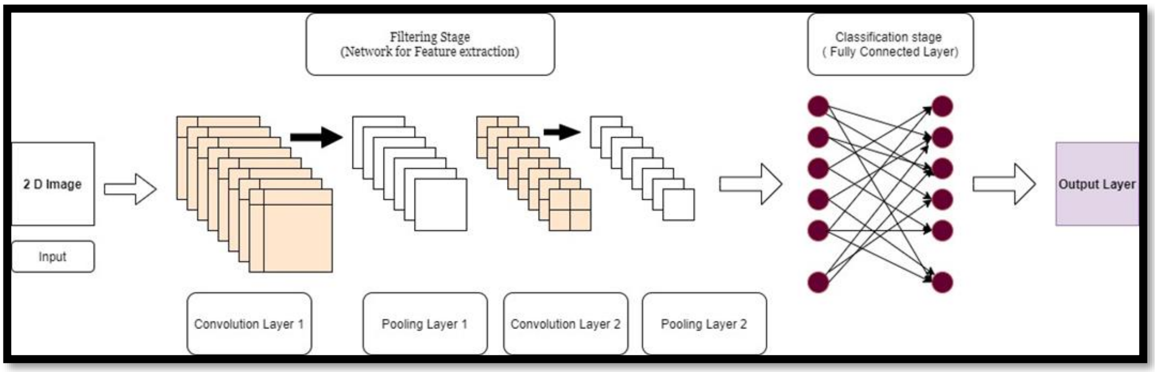

Figure 13: Architecture of 2-D CNN

From the literature, there are significant applications of deep learning approaches fault diagnosis. On the other hand, these deep learning methods required a large labeled dataset for training and testing purpose and the computational complexity is also very high. To overcome these drawbacks, the advanced approach of CNN, 1-D CNN is proposed which is less complex in computation as 1-D data is processed in CNN layers.

6.2 1D CNN

The proposed method of 1-D CNN is the advance approach of 2-D CNN. 1-D CNN works on a 1-D signal. Similar to the conventional 2-D CNN architecture, 1-D CNN also comprises two layers. Figure 14 shows the architecture of 1-D CNN. The first layer is called the convolutional layer in which both 1-D convolution and sub-sampling occurs and the second layer is MLP layer (Multi-Layer Perceptron) which is identical to a fully connected layer in conventional CNN method.

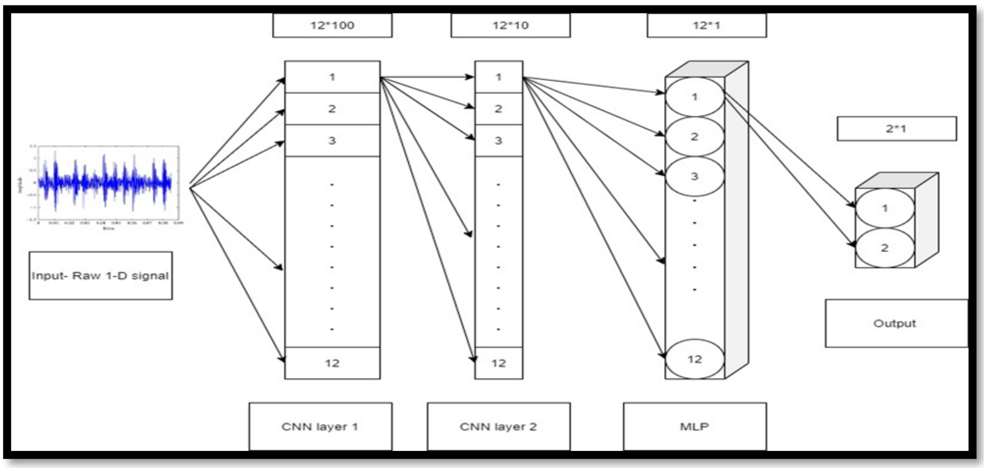

Figure 14: A sample of 1-D CNN consisting of 2 CNN layer and 1 MLP layer

Both the process of feature extraction and classification are done in a single learning body in 1-D CNN which eliminates the requirement of manual feature extraction. In each hidden convolution-pooling layer, a series of multi-scale sub-band decompositions are performed by the CNN layer. Due to this special decomposition,1-D CNN gets an ability to segregate the target pattern, it can be of any size and even any type of irregularity pattern in the 1-D signal. The ability to isolate the required pattern does not depend on the size of the object, anomaly, and time-frequency range of the signal.

In 1-D CNN, the signal of vibration is divided into various sub-bands into several sizes and scales. After this process, the 1-D CNN layer learns to isolate the pattern of irregularity from the regular pattern of the normal signal. For 1-D CNN some hyperparameters exist which describe the structure or architecture of 1-D CNN. These hyperparameters are determined by the trial-and-error method. These hyperparameters are as follows:

Hyperparameters of 1-D CNN architecture
1. Hidden convolution-pooling (CNN) layers
2. Hidden MLP layers
3. Neurons in CNN and MLP layers
4. Size of filter kernel
5. Sub-sampling factor
6. The choice of pooling and activation functions

Adaptive 1-D CNN is successful in both feature extraction and classification of fault data. In this design, how many layers will work can be decided practically and any number can be taken then adaptively selection of number of MLP is done by factor of sub-sampling and it automatically decides dimension of feature map. The process of feature extraction, as well as classification of the fault of rolling element bearing, are integrated with a single 1-D CNN. During CNN model training session, to minimize the error and to maximize the performance of the classification layer, the backpropagation (BP) algorithm is optimized using a gradient descent optimization method. In the input layer of 1-D CNN there is no requirement of manual handling of features or input data. 1-D CNN layers adapt the data and the hidden neurons of the convolution layer perform feature extraction and sub-sampling by kernel size and feature map. The function of MLP layer is classification of faults. The output of the CNN layer is transferred in the MLP layer in which the 1-D convolution of the 1-D signal with kernel filter is performed. There is no matrix operation in 1-D CNN. It is done by forwarding propagation (FP) and backward propagation (BP) which requires simple 1-D array operations.

Similar to conventional CNN (2-D), the input layer of 1-D CNN is also passive. The input to this passive layer is a raw 1-D signal. The output layer in the model is the MLP layer. In figure 15, three consecutive CNN layers are shown in which the size of the kernel in one dimension is 3, and the sub-sampling factor size is 2. A series of convolutions is performed by k^{th} neuron of first hidden CNN layer. Then the sum of these convolutions is further forwarded by activation functions f and then operation of sub-sampling occurs. The main difference between 1-D CNN and conventional CNN (2-D) that in 1-D CNN only 1-D arrays are used for kernel and feature map rather than 2-D matrices.

6.3 Mathematical Modeling for 1D CNN

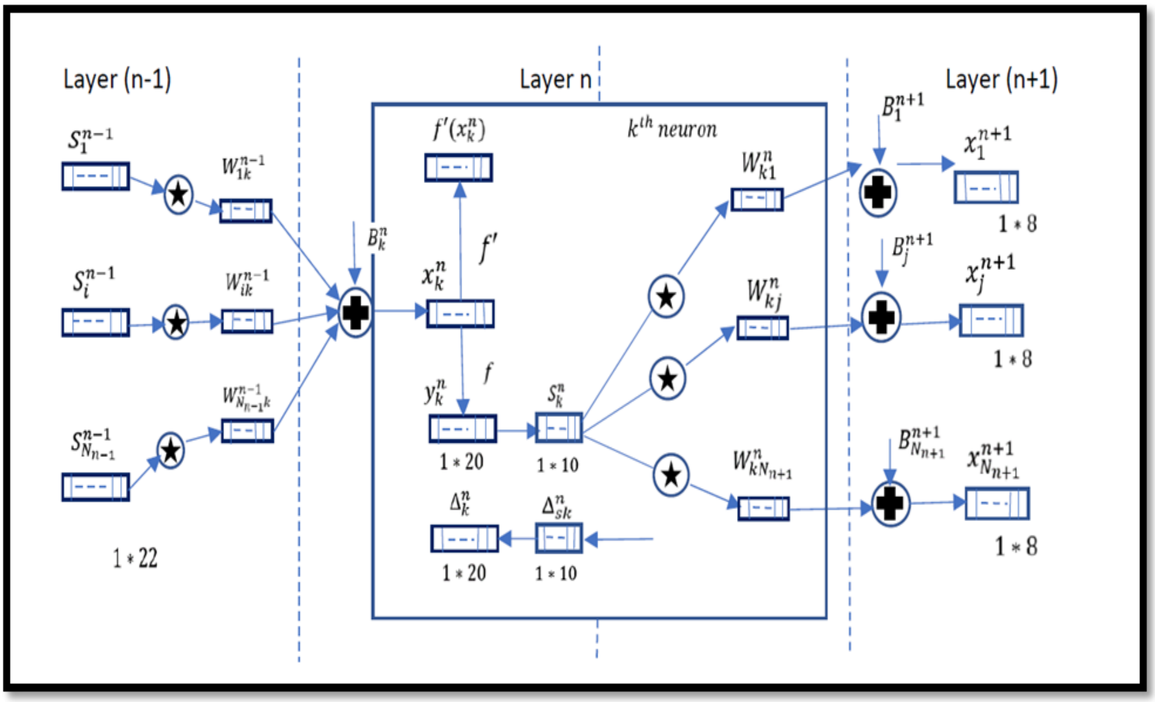

Figure 15: Hidden CNN layers of 1D CNN

The first step in the model is to assign weights to neurons in layer followed by defining bias for CNN layers. Forward propagation is used as the output which is obtained by the CNN layer (*n*-1) is the input in the next hidden CNN layer *n*.

$$x_k^n = B_k^n + \sum_{i=1}^{N_{n-1}} conv1D(W_{ik}^{n-1}, S_i^{n-1})$$

Where,

x_k^n - input in layer n from n-1 layer,

B_k^n - bias of k^th neuron at n-1 layer,

W_{ik}^{n-1} - kernel from an i^th neuron at n-1 layer to the k^th neuron at n layer,

S_i^{n-1} - output of i^th neuron at n-1 layer.

From figure 15, the output y_k^n is derived from the input x_k^n of layer n,

$$y_k^n = f(x_k^n) \text{ and } S_k^n = y_k^n \downarrow ss$$

Where output by a neuron is S_k^n and then down-sampled by $\downarrow ss$ operation with factor ss. For error, backpropagation (BP) initiates from the output of the MLP layer. Let n = 1 is taken to show input layer and n = N is taken to show output layer. Now, in the database, the number of classes can be taken as N_n.

The input vector is p, and its target vector is t_i^p and output vectors are $[y_1^N, \dots \dots, y_{N_n}^N]$. For input p, the mean-squared error (MSE) in the layer of output, E_p, is defined as:

$$E_p = MSE\left(t_i^p, \left[y_1^N, \dots \dots, y_{N_n}^N\right]\right) \sum_{i=1}^{N_n} (y_i^n - t_i^p)^2$$

There are some errors in the model due to network parameters. The main motive of backpropagation is the minimization of the contribution of network parameters in errors. For minimization of error, the derivative of MSE is computed concerning the individual assigned weight which is connected to that particular neuron, k. The optimization technique is used to reduce the contribution of parameters of network for error. By using the chain rule of derivative, the bias and weight of the neurons can be updated as follows:

$$\frac{\partial E}{\partial W_{ik}^{n-1}} = \Delta_k^n y_i^{n-1} \text{ and } \frac{\partial E}{\partial b_k^n} = \Delta_k^n$$

Regular or scalar backpropagation is executed from the last MLP layer (layer n+1) to the last convolutional layer (layer n).

$$\frac{\partial E}{\partial S_k^n} = \Delta S_k^n = \sum_{i=1}^{N_{n+1}} \frac{\partial E}{\partial x_i^{n+1}} \frac{\partial x_i^{n+1}}{\partial S_k^n} = \sum_{i=1}^{N_{n+1}} \Delta_i^{n+1} W_{ik}^n$$

When the first BP is executed, again back propagation is done towards input delta, Δ_k^n.

Let up-sampled map zero order can be described as:

$$uS_k^l = up(S_k^l)$$

Now, for backpropagation to input delta is,

$$\Delta_k^n = \frac{\partial E}{\partial y_k^n} \frac{\partial y_k^n}{\partial x_k^n} = \frac{\partial E}{\partial uS_k^n} \frac{\partial uS_k^n}{\partial y_k^n} f'^{(x_k^n)} = up(\Delta S_k^n) \beta f'(x_k^n)$$

Where $\beta = (SS)^{-1}$

For defining the BP of delta error, equation is described as:

$$\Delta S_k^n = \sum_{i=1}^{N_{n+1}} conv1Dz(\Delta_n^{n+1}, rev(W_{ki}^n))$$

Where,

'rev'- reverse the array,

'Conv 1Dz*'* – full form convolution in 1D,

Weights and bias sensitivities can be computed as:

$$\frac{\partial E}{\partial W_{ik}^n} = conv\ 1Dz\ (S_k^n, \Delta_n^{n+1})$$

And

$$\frac{\partial E}{\partial B_k^n} = \sum_n \Delta_k^n(n)$$

After computing weights and bias sensitivities, these are usedto revise weight and bias with learning factor, ε,

$$W_{ik}^{n-1}(t+1) = W_{ik}^{n-1}(t) - \varepsilon \frac{\partial E}{\partial W_{ik}^{n-1}}$$

$$B_k^n(t+1) = B_k^n(t) - \varepsilon \frac{\partial E}{\partial B_k^n}$$

For each backpropagation (BP) iterations, the steps are as follows in table 2:

Table 2: Steps for backpropagation iterations

1. FP	Forward propagation towards the output layer from the input layer	For determining output from each neuron by each layer, $y_i^n, \forall i[1, N_n]$ and $\forall n \in [1, N]$
2. BP	Finding delta error at output layer	To find delta error $\Delta_i^n, \Delta k \in [1, N_n]$ and $\forall n \in [2, N-1]$
3. PP	Post-processing	for computation of weight and bias sensitivities
4. Update	Update or revise weights and bias	$W_{ik}^{n-1}(t+1) = W_{ik}^{n-1}(t) - \varepsilon \frac{\partial E}{\partial W_{ik}^{n-1}}$ $B_k^n(t+1) = B_k^n(t) - \varepsilon \frac{\partial E}{\partial B_k^n}$

Chapter 7

Result and Discussion

The 1D CNN is a proposed technique or approach used for bearing fault detection and classification system. For the experimentation the system has a simple configuration for 1D CNN architecture consisting only two convolutional layers and one MLP layer in which 60 and 40 neurons are assigned to two convolutional layers respectively. And the MLP layer is having 30 neurons in the architecture. Now the input of 1D CNN is raw signal samples of the bearing vibration data of the MFPT dataset. The accelerometer in the test rig. is used to get raw vibration 1-D signal for the input of the 1-D CNN model. When the ball element makes contact with fault at any race of the bearing, hitting impact changes corresponding frequency and vibration spectrum deviates with some degree. By using MATLAB for this work, the raw 1-D signal is pre-processed and passed through the input layer which is a passive layer. Figure 16 shows the raw 1-D vibration signal for three conditions of a ball bearing which is the input of our test. This raw vibration signal is recorded for three different conditions, first is when the fault is embedded at the outer race of bearing (figure 16(a)), the second case is of the inner race fault (figure 16(b)) and the third case is for a normal (healthy) bearing (figure 16(c)). This data has been taken from the MFPT dataset. CNN layers decide the filter kernel size and feature map.

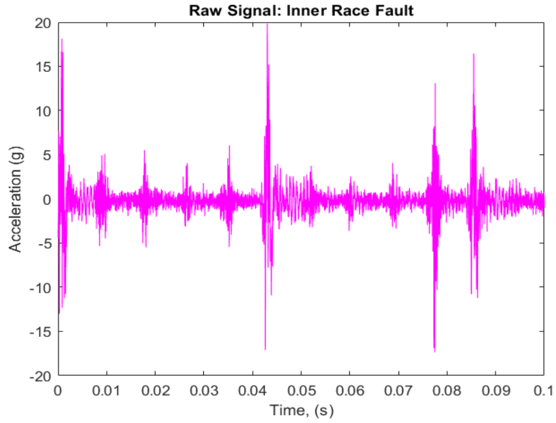

Figure 16 (a): Raw vibration signal of fault at inner race

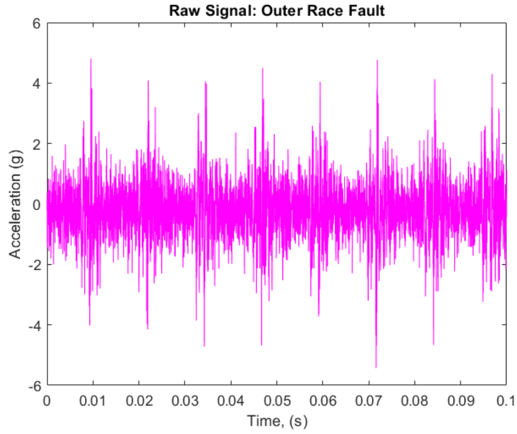

Figure 16(b): Raw vibration signal of fault at outer race

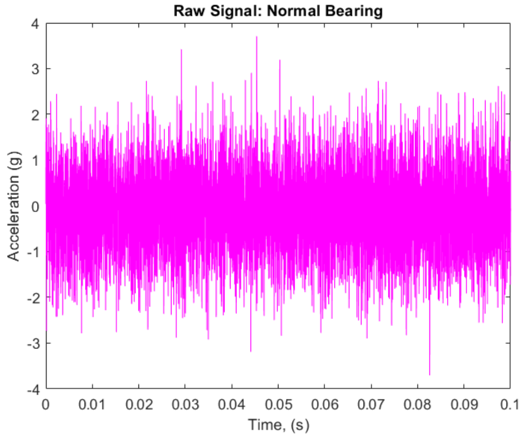

Figure 16(c): Raw vibration signal of normal bearing

This raw data of vibration is converted in the frequency domain which is easy to process in the CNN layer for feature extraction. In this work we have mainly focused to perform our analysis for a fault embedded at the bearing inner race. To get clear visualization of raw data, the vibration data is converted into the frequency domain as shown in figure 17.

In this dataset which is used for testing, affected frequency is BPFO, the fault is embedded in the outer race of the ball bearing. Figure 17 shows the frequency domain signal of a bearing which is an inner race fault bearing. The frequency spectrum is then zoomed in at a lower frequency range to get a close and clear view of the frequency-power spectrum at BPFI and the first few harmonics. By analyzing the time domain data (figure 18), it is observed that the amplitude of the raw signal is moderated at a specific frequency and the specific modulation frequency is 1/0.0009 Hz. The frequency of rolling element striking at the inner race fault is termed as BPFI, which is 118.875 for our test bearing. This shows that the bearing faults are in the inner race of bearing.

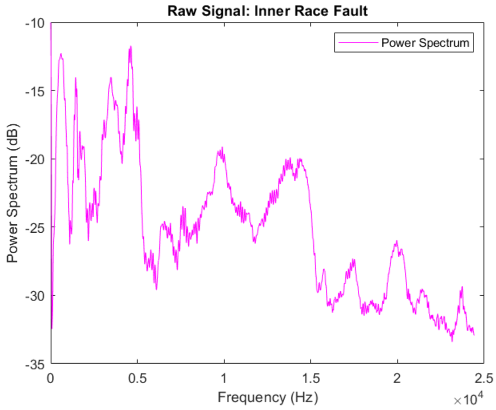

Figure 17: frequency-domain conversion of raw signal of inner race fault bearing

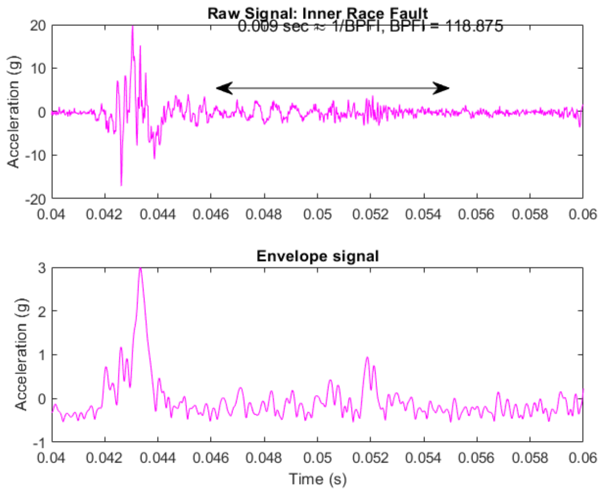

Figure 18: time domain and envelope signal for BPFI

The signal is then enveloped shown in figure 19 which describes the peak change clearly by removing the noise from the signal. The CNN layer extracts the feature by convolution followed by sub-sampling. And adaptively selects the feature according to which the class will be decided. The envelope spectrum of normal bearing is given to compare the difference in signals of vibration.

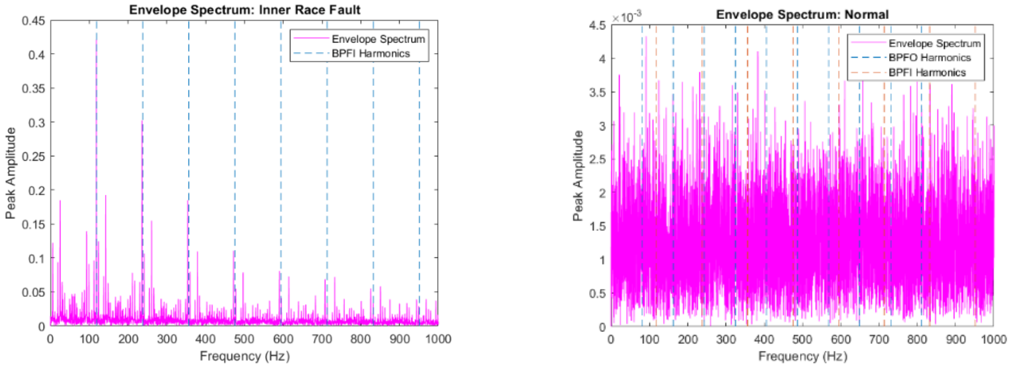

Figure 19: Envelope Spectrum

The envelope signal shows that most of the energy is primarily focused at BPFI and harmonics of BPFI which indicates that the fault is at the inner race and it also matches the fault type of the data. There is no change in peaks at BPFO and BPFI in envelope signal of normal bearing which shows the healthy condition of the bearing. by analyzing the frequency domain and time domain spectrum, it’s not necessary to get accurate results for bearing faults.

With the help of signals in the time domain, kurtosis is calculated for bearing vibration data. For a random variable, its fourth standardized moment is termed as kurtosis. with the help of kurtosis, the impulsiveness of the signal can be measured or the heaviness of tail of the random variable can also be categorized. In this test the classification is based on the feature termed as kurtosis. From figure 20, the kurtosis for the inner race is different from normal or healthy bearing. Figure 20 classifies the signal image of kurtosis for outer race fault of bearing, healthy or normal bearing, and inner race fault bearing. The impulsiveness of the signal for inner race fault is significantly larger and when this signal is enveloped, the spectrum analysis shows the signature of fault at BPFI. For the signal for fault at the outer race, the modulation of amplitude or impulsiveness of the signal at BPFO is very low and difficult to notice as it is covered by noise. There is no heaviness or impulsiveness or amplitude modulation for the normal bearing signal. The location of the fault is now found by calculating the frequency where the impulsiveness of the signal is present.

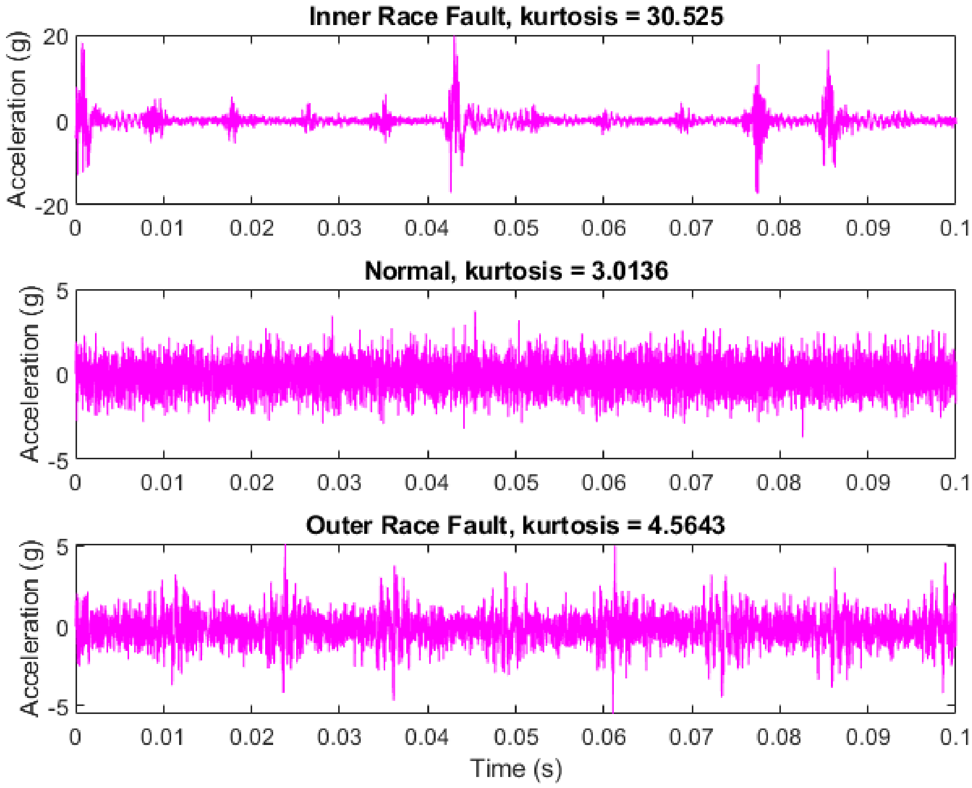

Figure 20: kurtosis-based classification

As the signal for outer race fault is covered with noise, Kurtogram and spectral kurtosis are computed to extract the signal with the highest kurtosis and further envelope spectrum analysis is performed to analyze the filtered signal. Kurtosis is computed within local bands of the frequency with the help of Kurtogram and spectral kurtosis. Kurtogram and spectral kurtosis are robust and powerful tools that can find and define the frequency band of the highest signal-to-noise ratio or the frequency band of the highest kurtosis value. After finding the highest kurtosis value frequency band, for obtaining other impulsive signals for analyzing the envelope spectrum, the bandpass filter is employed with raw vibration signal. The Kurtogram in figure 21 shows that at 1.5259 kHz the frequency band is centralized with a bandwidth of 1.0172 kHz this frequency band has the highest kurtosis of 2.8685 kHz. The optimal window length is further used to compute spectral kurtosis.

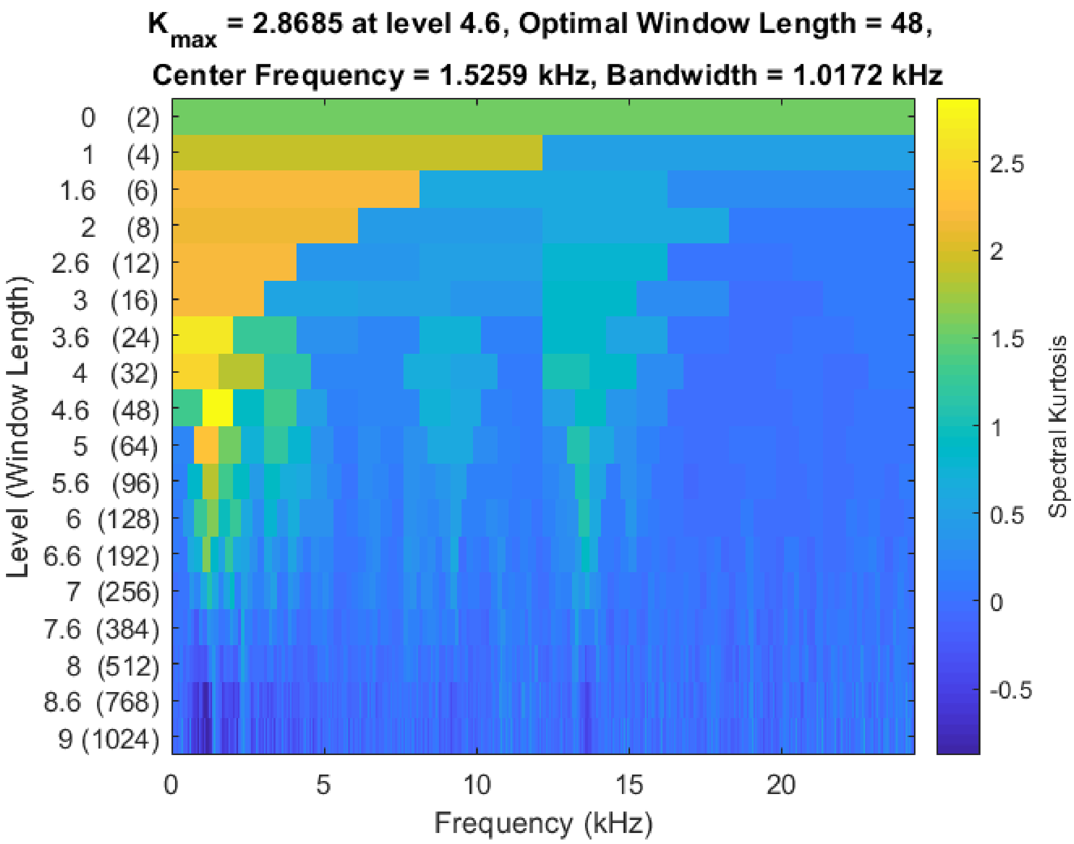

Figure 21: Kurtogram to find highest kurtosis frequency band

As the MFPT dataset of vibration data of bearing is used in this work, 75% labeled data of the dataset is used for training, and 25% labeled data of the dataset is used for the testing of the system. After training sessions of the system, the classifier is used in the system to classify the three different bearing conditions of inner race fault bearing, outer race fault bearing, and normal bearing. A valid and strong feature is used to classify the bearing fault condition and this feature is the log ratio of the amplitudes of BPFI and BPFO. To simplify the understanding of classifier, a very simple classifier is mentioned below:

- If $\log\left(\frac{BPFI\ amplitude}{BPFO\ amplitude}\right) \leq -1.5$: the fault embedded at the bearing outer race
- If $-1.5 \leq \log\left(\frac{BPFI\ amplitude}{BPFO\ amplitude}\right) \leq 0.5$: the bearing is in normal condition
- If $\log\left(\frac{BPFI\ amplitude}{BPFO\ amplitude}\right) > 0.5$: the fault embedded at the bearing inner race

For validating the classifier, the testing is done with 25% labeled data of the dataset and the log ratios of the amplitude of BPFI and BPFO are correctly describes the accuracy of the system. The impact of classification matrices is found using evaluation matrices. The result obtained from the data can be presented in terms of evaluation matrices. Generally, perfection and exactness can be defined in two classes, Healthy (H) and Faulty (F) for any machine element but specific matrices, classes are mentioned as true positive [TP], true negative [TN], false-positive [FP], and false-negative [FN]. These matrices result directly reflect the impact on condition monitoring requirements.

The evaluation matrices are computed as follows:

		Result
Accuracy	$Acc = \frac{[TP] + [TN]}{[TP] + [TN] + [FP] + [FN]}$	98.9%
Sensitivity	$Sen = \frac{[TP]}{[TP] + [FN]}$	95.9%
Specificity	$Spe = \frac{[TN]}{[TN] + [FP]}$	98.1%
Positive Predictivity	$Ppr = \frac{[TP]}{[TP] + [FP]}$	96.1%

The proposed approach of 1-D CNN in this work accomplished the objectives as approach gives results with high accuracy as compared to traditional methods. For real-time condition monitoring, the computational complexity of 1-D CNN is low. The reason for low computational complexity is to apply the 1-D arrays for diagnosis of fault instead of 2-D matrices 1-D CNN. There is also a low time delay in fault identification. Ordinary hardware can be used for 1-D CNN, which cannot be used in 2-D CNN.

Chapter 8

Conclusion and Future Work

8.1 Conclusion

To overcome all the disadvantages of traditional methods for fault diagnosis of ball bearing, 1-D CNN approach is used in this work.

- A 1D CNN architecture and algorithm are used to facilitate the automatic extraction of features from the lengthy signals of vibration. The proposed system of 1D CNN has the special ability to learn and extract the features after proper training of algorithms and it can be employed with any bearing data. There is no requirement of using complex architecture of 1D CNN system.
- 1-D Convolutional Neural Network (1-D CNN) is developed for the identification and classification of faults embedded in any of the race of ball bearing. The raw vibration data is taken from open source MFPT dataset.
- A 1-D CNN architecture was designed in which convolutional layers and sub-sampling layers and MLP layers. 75% of label datasets from the database are used for training of the above network and 25% data of dataset is used for testing the model.
- The adaptive design of the 1-D CNN presents an ability to fuse extraction of features and classification of fault in a single learning body. 1- D arrays are used in this model which leads towards less computational complexity.
- 1-D CNN is well suited for real-time problems and applications because of its low computational complexity requirement.

- For getting higher accuracy, this approach can be implemented for real-time condition monitoring of bearing.
- With the training of back propagation (BP) convolutional layers of 1D CNN architecture can learn feature extraction of optimized features and the MLP layer is used for classification of the fault. The fault detection accuracy of the system is greater than 98.5% which indicates that this approach and system can be used for real-time condition monitoring of bearing.

8.1 Future work

The hardware implementation of the proposed system for real-time condition monitoring and the extension in this system by compiling other techniques with 1D CNN (Hybrid System) for monitoring the different types of faults of different intensities will be the scope in the future work.

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   Authors: Pragya Sharna, Swet Chandan

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