Fault diagnosis of a rotor-bearing system using acoustic sensors and machine learning techniques

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ABSTRACT

Due to the need for higher reliability and reduced production loss caused by rotor-bearing machine faults, vibration and acoustic-based condition monitoring is becoming increasingly important in the industry. Many machine fault diagnostic techniques include automatic signal categorization to improve accuracy and reduce machine faults. In this paper, machine learning techniques are used to identify the fault of a rotor bearing system. These techniques require raw time-domain data from the machine's sensors to be first processed and then turned into parameters using Fast Fourier Transform, and Mel spectrogram. Experiments have been performed in which different types of individual and mixed faults like angular misalignment, horizontal misalignment, unbalance rotor, eccentric rotor, and cocked rotor are studied. Bearing forces, noise signals, and shaft deflection are measured using force sensors, microphones, and proximity sensors, respectively. The diagnosis result shows that the proposed techniques recognize different fault categories, mixed or compound faults, and the effectiveness of these techniques.

INTRODUCTION

Rotating machinery condition monitoring assists in early fault detection and problem anticipating to avoid complete failure. Bearing and unbalanced vibration can produce noise and reduce a product line's quality. Even the entire rotor bearing system may malfunction as a result of severe bearing vibrations, which would result in system downtime and financial loss for the customer. Research on diagnosing problems in the rotor-bearing system is continuing, and numerous advancements are yearly published in a variety of conferences and journals. Despite the excellent level of durability of modern rotating machines, the desire for ever greater operation and fewer unplanned maintenance is posing new hurdles for the industry. A recent illustration of this demand may be found in the airline sector, which is currently pressuring manufacturers to enable quick turnaround times and extend aircraft flight hours to increase cost-benefit. The rotor dynamic problems described in this research still need to be taken into account in the drive for better reliability and optimized maintenance procedures quite apart from the high degree of reliability . Despite being the most precisely manufactured components, rolling element bearings could fail before their time if disturbing forces are applied**.** Bearing problems are probably dangerous and can harm the productivity level and the tools. As a result, these bearings' condition monitoring and fault diagnostics have become crucial study areas for advancement and industrial applications**.** As the main basis, faults are created and multiplied during bearing operation. These faults often occur in rolling parts like the balls and internal and exterior races. Before expanding, it's critical to do an early fault diagnosis**.** For rotor bearing systems, vibration and acoustic signals can be taken into consideration while implementing various condition control systems**.** The fault detection of the rotor bearing system has made use of a variety of artificial intelligence (AI) approaches, including artificial neural networks (ANN), support vector machines (SVM), random forests (RFC), K-nearest neighbour (KNN), and linear discriminant analysis (LDA)**.** In this paper, authors have used the CNN algorithm to detect broken rotor bars in an induction motor**.** The induction motor used in their experiment was tested with no faults, one broken bar, two broken bars, and three broken bars. To obtain the signal, they estimated the frequency spectrum for fault detection using stator current**.** For feature extraction, the rotating machine's time-domain vibration signal with both healthy and damaged gears was processed. This audio classification approach is used in this paper for preprocessing the dataset **.** There are lots of defects present in the rotor-bearing system such as unbalance, misalignment, looseness, fluid-induced instability, bearing faults, shaft cracks, blade cracks, rotor bow. One of the most prevalent rotor dynamics defects is unbalancing. Every rotating machine has a certain amount of unbalance by nature. In an experimental setup unbalance can be added from outside in the form of small masses. Misalignment is another common fault that has the potential to seriously harm rotating types of equipment. For this work faults must be constrained because research on rotor dynamic faults encompasses a vast area. Therefore, the following faults are the only ones covered in this paper.

(i) unbalance,
(ii) horizontal misalignment,
(iii) angular misalignment,
(iv) eccentric rotor

This research primarily focuses on the classification of bearing faults utilising machine learning techniques CNN. Sensors and microphones are used to capture vibration data in time domain signals for both non faulty bearings and bearings with various faults (mentioned above).

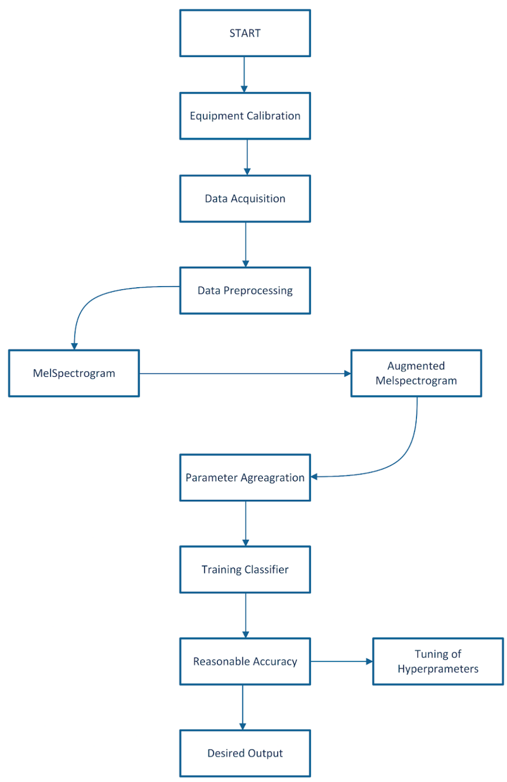

Figure 0. Flow chart of faults of rotor bearing system health diagnosis

In this paper, the first step that was performed was to set up the equipment for the experiments and calibrate them properly. Then the Real time domain data was recorded by performing the experiments which was later pre-processed to remove the unnecessary data. The obtained time domain data was then converted to parameters by performing Fast Fourier Transform, Mel spectroscopy. These parameters were then pre-processed and were used to train the classifiers. if a model didn't give reasonable accuracy, then we perform hyper parameter tuning for that given model to increase its performance.

Experimental setup

The experimental set-up for the study, which is shown in the given figure 1, is mounted on an aluminium base plate that is put on a wooden foundation that is fastened with bolts. To reduce vibration responses from the ground, the base plate has been isolated with the aid of aluminium packing and a rubber damper mounted on bolts. The experimental setup consists of a shaft supported by rolling element bearings and driven by a DC motor with an external speed controller. Two sensors and a microphone were used to pick up the vibration signals and acoustics signals at the following locations shown in figure 2.

1. Shaft displacement in the vertical direction at the middle of the shaft using the proximity sensor.
2. Bearing force direction in the vertical direction at right side bearing using the piezoelectric sensor.
3. Noise signal near the left bearing using the microphone.

Experiments were carried out on a rotor-bearing fault simulator, which is made up of a shaft supported by two roller bearings and driven by a DC motor. A flexible coupling is used to connect the rotor shaft to the motor shaft. One disc is mounted on the left-hand side from the middle of the shaft. The real-time data is collected using a data acquisition system (DAQ) and using simcenter software.

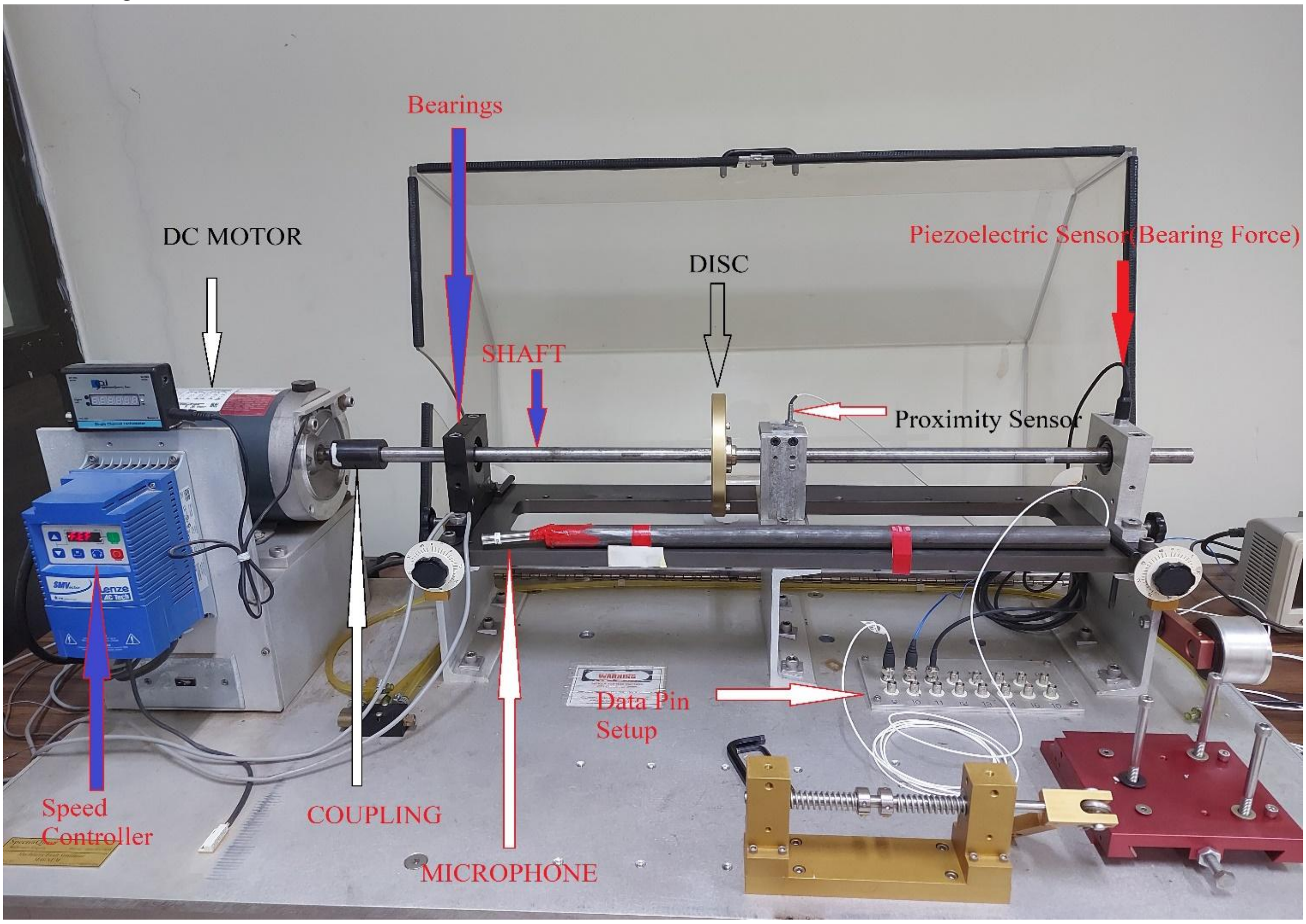

Figure 1. Experimental setup of rotor bearing system

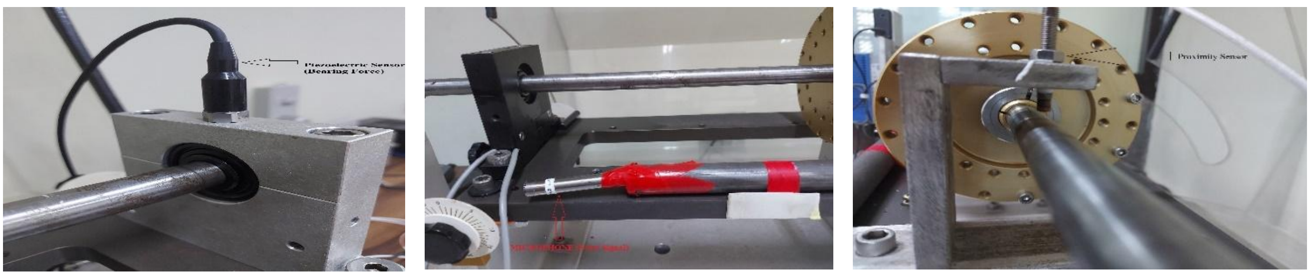

Figure 2. The different sensor locations on the rotor bearing system

DATA PREPROCESSING

The dataset was divided into three parts, Pressure, Displacement and Force. The columns were named NON_FAULTY, RIGHT_AND_LEFT_BEARING, Right_Bearing and UNBALANCE_FORCE in all the datasets.These three datasets were imported separately and On each of their columns Fast Fourier Transform were applied and The data obtained have been plotted in figures 3-6 with a time frame of 1 second (12500 frames). It was observed that they were showing good variation even for small time intervals. Therefore, it is not possible to simply make a Mel Spectrogram and apply CNN since each node would get split several parts due to FFT, and this would lead to data loss and hence, a poor accuracy. This is why the columns were first converted into sound signals. The sample rate for constructing the sound signals from columns was set to $\frac{1}{7.8e-5}$ because the sensor was collecting data with a time period of 7.8e-5s for a time interval of 30s.

An envelope function which removes dead space from the signal.The dead spaces were removed with a threshold of 0.0005 and the signal Mel Spectrogram and FFT were visualized again. The clean signals were according to their respective classes.

The distribution of data with respect to Class 1, Class 2, Class 3 and Class 4 was visualized.

- Class 1 : Non-Faulty
- Class 2 : Right and Left Bearing Fault
- Class 3 : Right Bearing
- Class 4 : Unbalanced Force

Load the clean audio. Then, changed the channel of audio to Channel 2. Then changed the sample rate of audio to 12,800 to 44100. Pad (or truncate) the signal to a fixed length '2000' in milliseconds. Then shifted the time by 0.1 second, to remove initial noise present in the data. Then, the new signal after preprocessing plotted in figures 7-9 with comparison of original audio.

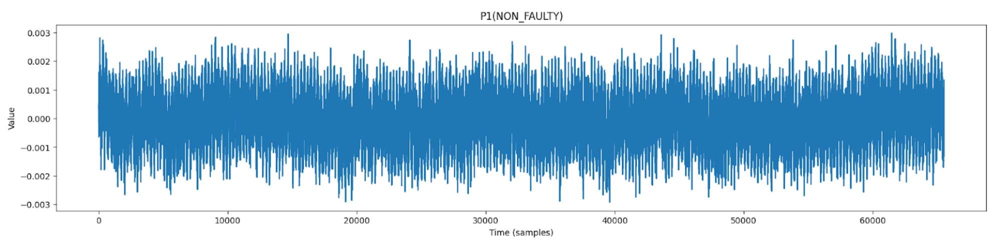

Figure 3. Time Response graphs for a No fault Rotor.

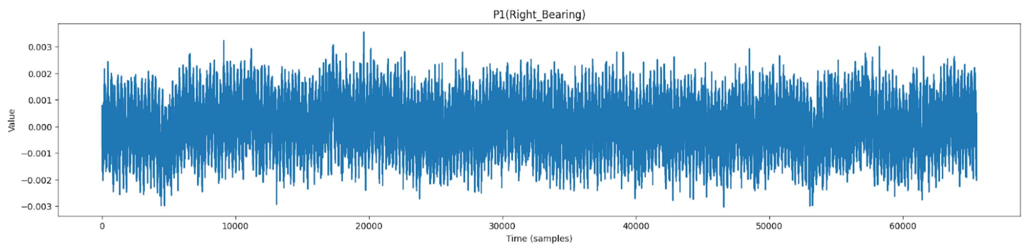

Figure 4. Time Response graphs for a right-bearing fault.

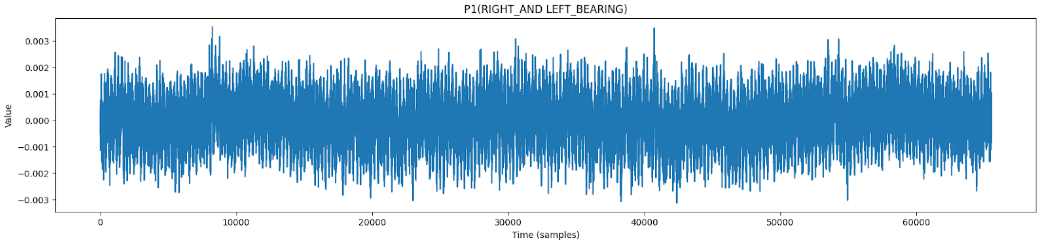

Figure 5. Time Response graphs for a Right Left Fault.

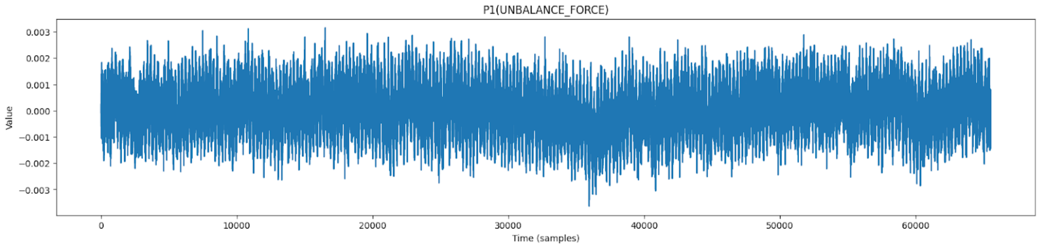

Figure 6. Time Response graphs for an Unbalanced Rotor

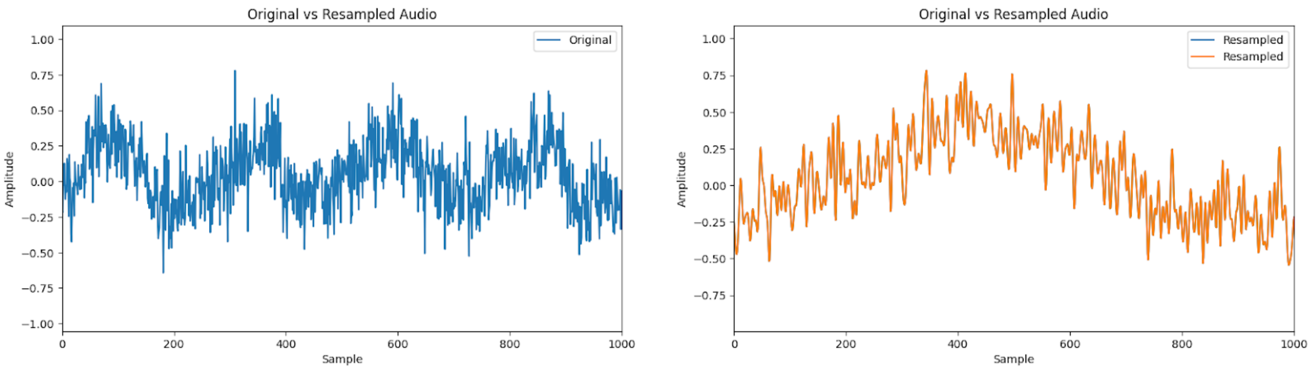

Figure 7. Original V/s Resampled for No fault Rotor.

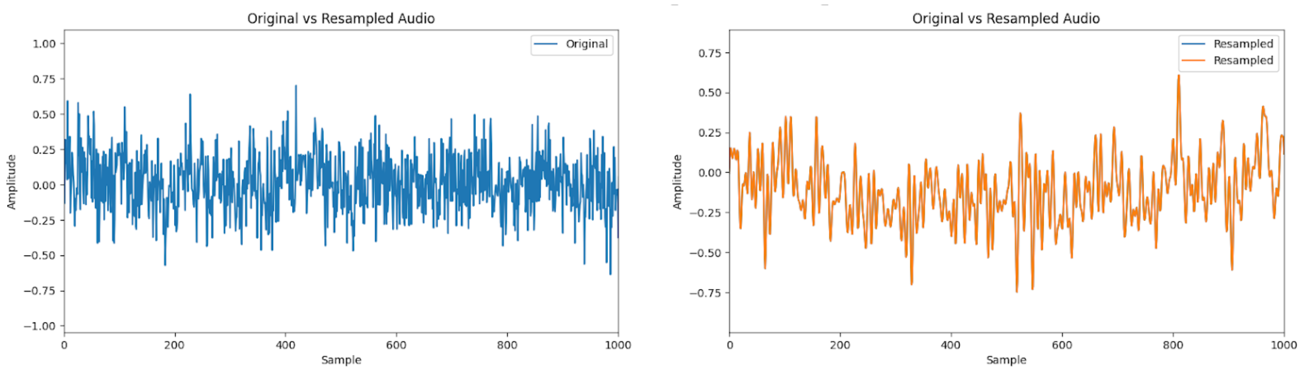

Figure 8. Original V/s Resampled for a right-bearing fault.

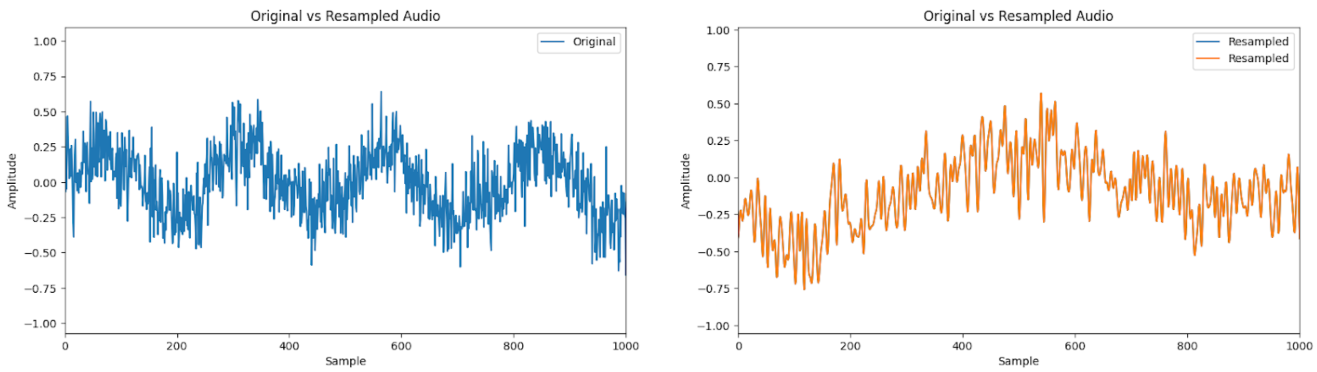

Figure 9. Original V/s Resampleds for a Right Left Fault.

PARAMETER GENERATION

The Raw Time-Domain data from the machine's sensor is used to generate parameters for the machine learning process which is processed using a fast Fourier transform, Mel spectrogram. Here, Librosa Module has been used to generate the parameter which has been processed as follows. In order to prepare audio data for deep learning models, we need to convert it into a format that can be easily processed. One useful way to do this is by creating a Mel Spectrogram, which captures important features of the audio. To further improve the quality of our data, we can use data augmentation techniques, such as SpecAugment. SpecAugment involves randomly blocking out ranges of frequencies (using frequency masks) or time (using time masks) from the Mel Spectrogram to increase variability in the data and improve the model's ability to generalize. Mel Spectrogram and SpecAugment mel spectrogram is plotted in figure 10-11. Overall, these techniques can help us create high-quality data that is suitable for training deep learning models on audio tasks. The train-test procedure is not appropriate when the dataset available is small. The reason is that when the dataset is split into train and test sets, there will not be enough data in the training dataset for the model to learn an effective mapping of inputs to outputs.

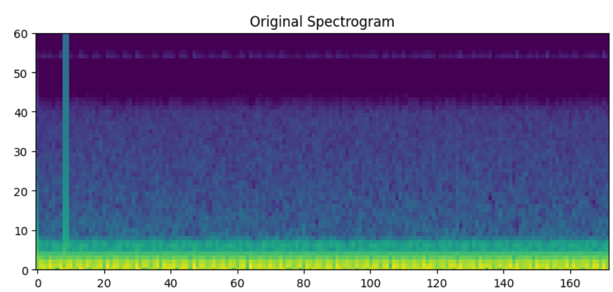

Figure 10. Mel Spectrogram

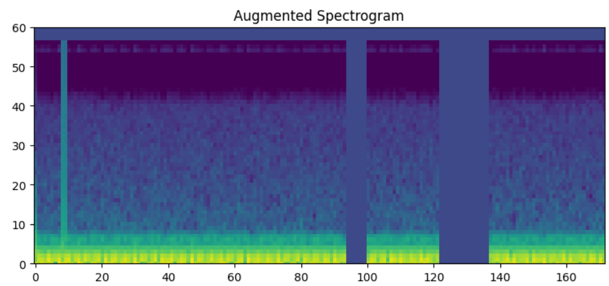

Figure 10. Augmented Mel Spectrogram

Model

Convolution Neural network

A Convolutional Neural Network (CNN) is a deep neural network that is widely used for image classification and computer vision tasks. The main building block of a CNN is a convolutional layer, which applies a set of filters to an input image to produce a set of feature maps. Each filter learns to recognize a particular type of feature in the input image, such as edges, corners, or textures.

The convolution operation involves sliding a small filter or kernel across the input data, performing an element-wise multiplication between the values in the filter and the corresponding values in the input data. The result of each multiplication is then summed up, and the sum is stored in an output array. This process is repeated for every location in the input data that the filter can be placed.

convolution formula:

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t - \tau)d\tau$$

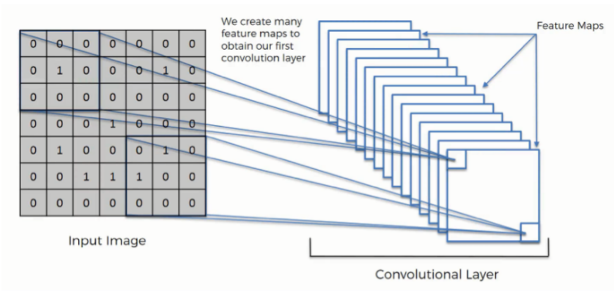

Figure 11. Convolution Layer

The ReLU function computes the maximum of the input value and zero, resulting in an output value that is always non-negative. This helps to introduce non-linearity into the network, which is essential for modeling complex relationships between the input and output.

$$R(z) = max(0, z)$$

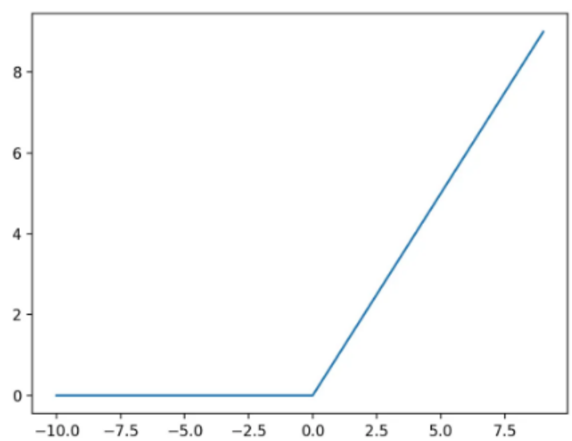

Figure 11. ReLU Activation Function

Batch normalization, which helps to improve the stability and convergence of the network. Batch normalization involves normalizing the output of each layer to have zero mean and unit variance, and then scaling and shifting the output using learnable parameters.

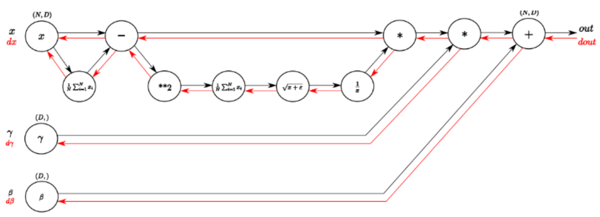

Figure 12. Batch normalization

Batch normalization helps to reduce the covariate shift problem, which can occur when the distribution of the input to each layer changes during training. This, in turn, helps to improve the stability and convergence of the network.

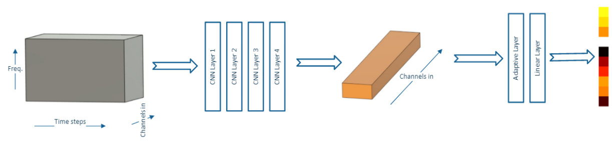

Figure 13. CNN Model

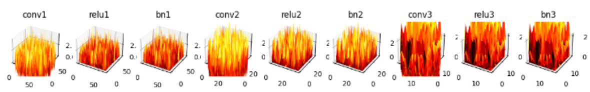

Figure 14. Activation Layers

PARAMETER TUNING

Hyper parameter tuning has been performed for different classifiers using Randomized search, which randomly picks up the parameters from the range provided and finds the best combination for the model.

Not all models need to be tuned as they were already performing well with default parameters. The parameters sets for different models are shown in Table 2.

Table 2.Different Layers in Model(Convolution Neural Network)

Layer	Output Shape
Input	(Batch_size,2,T,F)
Conv2d	(Batch_size,8,T/2,F/2)
ReLU	(Batch_size,8,T/2,F/2)
BatchNorm2d	(Batch_size,8,T/2,F/2)
Conv2d	(Batch_size,16,T/4,F/4)
ReLU	(Batch_size,16,T/4,F/4)
BatchNorm2d	(Batch_size,16,T/4,F/4)
Conv2d	(Batch_size,32,T/8,F/8)
ReLU	(Batch_size,32,T/8,F/8)
BatchNorm2d	(Batch_size,32,T/8,F/8)
Conv2d	(Batch_size,64,T/16,F/16)
ReLU	(Batch_size,64,T/16,F/16)
BatchNorm2d	(Batch_size,64,T/16,F/16)
Aaptiv Avg Pool 2d	(Batch_size,64,1,1)
Flatten	(Batch_size,64)
Linear	(Batch_size,10)

MODELS RESULTS

Convolution Neural Network model we train with an accuracy of 95% and Tested on dataset with Table 3 shows the classification accuracy w.r.t each class (Faults). 100% accuracy means our model reads the model properly and no loss in data happens. So its accuracy of the model to read data increases as we increase the size of the dataset.

Here, NF stands for No faults, RBF stands for Right bearing fault, RLF stands for Right Left fault and UFF stands for Unbalanced Force Fault.

Table 3. Classification accuracy for each class (Faults)

	NF	RBF	RLF	UFF
CNN	100%	100%	100 %	100%

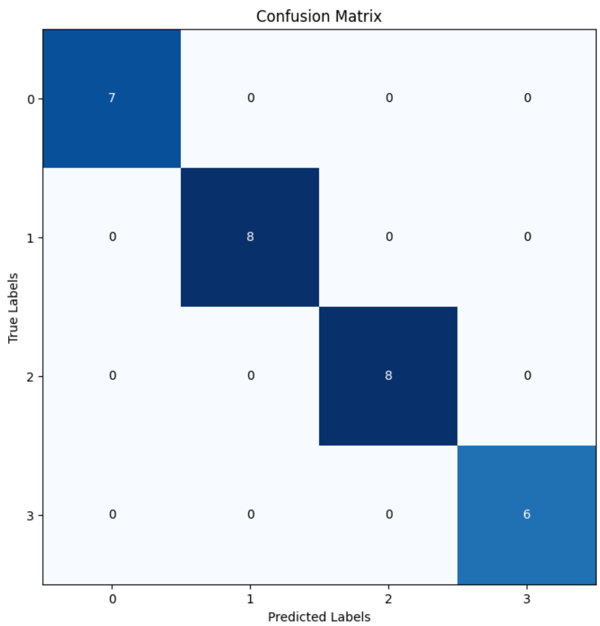

Figure 15. Confusion Matrix

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