Fault Diagnostics on Vibration Data of Taper Roller Bearing Using Deep Learning Algorithms

Mahesh S. Bankar
Department of Manufacturing Engineering and Industrial Management,
College of Engineering Pune, Maharashtra, India.
bankarm03@gmail.com

B. B. Ahuja
Department of Manufacturing Engineering and Industrial Management,
College of Engineering Pune, Maharashtra, India.
bba.mfg@coep.ac.in

Maneetkumar R. Dhanvijay
Department of Manufacturing Engineering and Industrial Management,
College of Engineering Pune, Maharashtra, India.
mrd.mfg@coep.ac.in

Abstract

Industries are looking for advanced maintenance techniques to reduce the cost of maintenance and increase the productivity of plants. Fault diagnostics is the focus area to reduce the downtime of the machine and ensure its durability. Bearing condition monitoring is important because bearings are the key component of rotary machines. Bearing failure detection relies heavily on vibration signal analysis. A defect in a rolling element causes the bearing to generate an impulsively responsive signal. This work contributes to the development of the framework to generate and acquire bearing vibration data. The data is collected for healthy bearing, bearings with cage damage, and ball damage. It generates a unique pattern of vibration signals for each bearing defect at constant, increasing, increasing and decreasing, and decreasing and increasing speeds. The data is post-processed using deep learning techniques capable of diagnosing and categorizing the different failure conditions. The paper proposes feature extraction and deep learning algorithms for diagnosing bearing faults. Feature extraction of signals is the traditional method of fault diagnosis, which involves expert knowledge and time. The 1D and 2D convolutional neural network (CNN) algorithms give an accuracy of 99%, which is far better than the feature extraction and artificial neural network (ANN) techniques, with an accuracy of 55%. Such techniques will help in the adaption of smart manufacturing in India.

Keywords
Industry 4.0, Deep Learning, Arduino Uno, Condition Monitoring, Python.

1. Introduction
In fourth industrial revolution, companies focusing on the adoption of technologies related to industry 4.0. The world has witnessed the rapid digital transformation during the last few months, and machine learning, preventive and predictive maintenance are the key focus areas to increase productivity. Machine maintenance is carried out fast when the fault diagnosis is done correctly, and localization of faults is also important to reduce downtime and increase Overall Line Efficiency (OLE). Unplanned production shutdowns caused by equipment failure are the most expensive hence, early condition monitoring and fault diagnosis (CMFD) is critical for ensuring production reliability.

1.1 Objective
Given the current need for the Indian manufacturing sector to adopt industry 4.0 techniques this work focuses on the maintenance and health condition monitoring of taper roller bearing using deep learning algorithms. The goal is to propose a method for acquiring vibration data from taper roller bearing and post-processing the data in order to develop a machine learning models. Different bearing fault conditions such as cage damage, ball damage, cage and ball

damage, and healthy bearing are executed here. The main objective of the project is to utilize vibration analysis to identify faults in bearing. The data is visualized and interpreted using a feature extraction technique. A comparative study for accuracy, fault classification results, and methodology for the development of deep learning algorithms has been carried out.

2. Literature Review

The tapered roller bearing has many industrial applications, bearing state determines the effectiveness of the equipment, which operates in a complex environment with varying conditions. As a result, there are numerous factors that can cause bearing faults (Xu and Yu 2020). Effective fault diagnosis is crucial for monitoring the operational condition and improving the security and reliability of rotating machinery in order to decer equipment maintenance costs (He and Ding 2016). Under similar working conditions, a ball bearing produces the least amount of vibration amplitude, whereas a tapered roller bearing produces the most. Hence, it is important to study and build a framework for condition monitoring and fault diagnosis for taper roller bearings (Rudrapati et al., 2017). Acoustic emission signals, motor current signals, and vibration signals are frequently used methodologies. The vibration signal-based method is the most popular approach among these bearing data types because vibration signals are easy to measure and provides health status of bearing with dynamic information (Kharche and Kshirsagar 2014; Chacon et al. 2015; Zarei et al. 2014). This research presents that even if a bearing is geometrically perfect, it vibrates during operation due to contact forces between different bearing parts. The presence of faults in various bearing parts produces a unique pattern of vibration response. As a result, many researchers have been looking into detailed investigations of the vibration responses of taper roller bearings under single and multiple defect conditions, as well as vibration pattern recognition techniques, to improve maintenance operations (Vara Prasad and Kumar 2015; Kumbhar et al. 2014). Traditional statistical feature extraction on time domain signal necessitate an expert knowledge and signal processing techniques. Statistical parameters such as crest factor, root mean square value, maximum value, skewness, mean value, and kurtosis can be determined using feature extraction, and the type of fault can be easily diagnosed. However, it takes time and the data must be interpreted correctly (Pratyusha et al. 2014; Shen et al. 2018). Feature extraction is done from time, frequency and power spectrum. All three features are combined to form a feature vector, which is then passed into support vector machine, K-nearest neighbors, and kernel linear discriminant analysis to diagnose faults. KNN gives a highest accuracy of 96% (Altaf et al. 2022). The vibration spectrum of healthy bearing is the benchmark for further analysis. A typical machine learning method includes data collection, feature classification, feature selection, and feature extraction (Prieto et al. 2013). The data is the source for building machine learning models. Data generated can be of three types: synthetic data, experimental data, and historical data. The challenging task here is gathering high quality data. When no historical data set is available for study, then synthetic and experimental data generation is the option used by many researchers. In this study, roller bearing simulations are done and synthetic and experimental vibration data sets are created for training deep learning algorithms (Kahr et al. 2022).

It was discovered during the literature review that many researchers used freely available Case Western Reserve University (CWRU) roller bearing data in their studies. Most recent study looked at vibration image generation methods, and the best results were obtained with an empirical mode decomposition-pseudo-Wigner-Ville distribution with an accuracy of 96.67 percent and a training time of 170.46 seconds (Fan et al. 2021). Because of its powerful capabilities, deep learning is increasingly being used in fault diagnosis. Deep learning, as opposed to traditional methods, uses non-linear activation functions with auto feature extraction and classification through each layer (Wang et al. 2021). ANN, 1D CNN, and 2D CNN being widely used in CMFD. Machine learning models developed using such algorithms are more accurate, fast, and reliable to implement in industries (Liu et al. 2022). An artificial neural network study is presented with and without preprocessing of data. The extracted features are then sent to the classifier. There is a need to make classifiers faster and more accurate for computer vision and machine learning applications (Samanta et al. 2006). In ANN weights are assigned to each connection formed between the input and output layers. Due to its network connections, it requires parallel computing power. The appropriate network structure is achieved through iterations (Mijwil 2018). In comparison to ANN, CNN reduces the number of parameters, i.e., it reduces the dimensionality of data using filters. As a result, researchers use CNN to perform larger and more complex tasks quickly (Albawi et al. 2017). Convolutional neural networks (CNNs) are a subset of deep learning that are known for their image recognition and classification capabilities. For bearing defect detection, researchers used one-dimensional (1D) and two-dimensional (2D) CNN models. 1D-CNN uses raw vibration data as input, which makes it fast. Given study provides an in-depth investigation of the general architecture and principles of 1D CNN, and 94% accuracy is achieved on a real bearing data set (Kiranyaz et al. 2021; Eren et al. 2019). In 2D CNN, the row vibration data can't be used directly; it is preprocessed and converted into vibration images of a given pixel size. Post processing is done for fault diagnosis on images. Deep learning models such as 2D CNN have the capability to learn discriminative features directly from vibration characteristic images (Nguyen et al. 2013). The proposed method does not require feature extraction and it directly produces diagnosis results with good accuracy in noisy environment. Time domain vibration signal is converted into image since it is easy to extract features from high dimensional data. The study is carried on CWRU bearing data (Hoang and Kang 2019). The following work discusses some of the challenges and opportunities in this domain. Real-world fault detection will become a significant challenge in the coming years as current machines evolve into larger and more complex systems. Deep learning requires large data samples with labels, which is typically hard to acquire in industries. Furthermore, imbalanced datasets are common in industrial settings, which means that the sample sizes for normal and faulty conditions are not the same (Saufi et al. 2019). Motivated by the above literature study, this paper developed a 2D CNN machine learning model for diagnosing bearing faults. The vibration data is collected at varying operational speeds of the taper roller bearing. This has generated the balanced and labelled vibration data. Then gray images are obtained from the time domain vibration signals. Through vibration image classification, image processing is being used to identify faults in bearings. Also, a comparative study of ANN and 1D CNN machine learning models was done on the same dataset. This paper is organized as follows: Section 3 brief about ANN, and CNN algorithms. Section 4 explains test setup and components involved. Data acquisition system is discussed in section 5. In section 6, results and graphs are shown, and finally, important conclusions are drawn in section 7.

3. Methods

3.1 Artificial Neural Network (ANN)

The first and most fundamental neural network in deep learning is the ANN. The ANN is programmed to perform specific tasks such as data classification and pattern recognition. Neural network is fundamental building block of artificial neuron. Inputs, weights, bias, summation function, activation function are the components of ANN. The neuron activation is govern by following equation:

$$x_i(m+1) = f(x_i(t), net_i(m+1)$$

Where, $x_i(t)$ is neuron activation value, f is function to activate, $x_i(m+1)$ is updated activation value, and $net_i(m+1)$ is net neuron input by rule of propagation (Marzi 2008).

3.2 Convolutional neural network (CNN)

CNN is cognitive approach that combines the operations of feature extraction and feature categorization. They can directly learn how to maximize features of raw input in training. CNN is a unique feed-forward-structured network applied in many domains such as speech recognition and image processing. A novel use for CNN is in signal analysis and recognition. 1D and 2D CNN are used here for vibration signal analysis. Figure 1 is for basic 2D CNN block diagram (Figure 1).

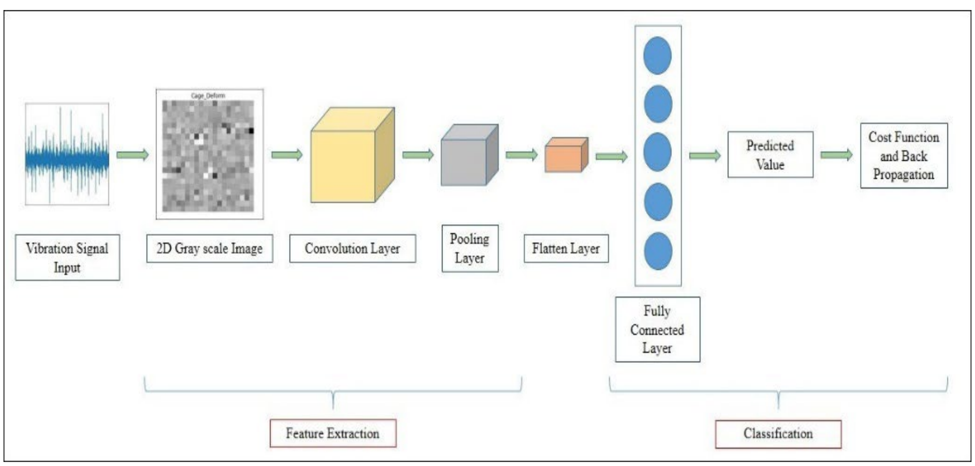


Figure 1. CNN architecture

3.2.1 Comparison between 1D and 2D CNN

Except the filter sliding mechanism 1D and 2D CNN has the same architecture. Kernel slides along length to extract the features, and it determines the convolutional points in 1D CNN. Whereas the 2D CNN filter moves the entire structure horizontally as well as vertically. For each step, convolution operation range is determined by width and height of the 2D filter. In 1D CNN, input and output data is two dimensional and mostly used on Time Series. Input and output data of 2D CNN is three dimensional mostly used on Image data. Batch normalization technique is used to avoid the batch wise shift of covariance and training acceleration. Also, drop out and early stopping techniques are used to avoid the overfitting of model.

4. Experimental Setup

Obtaining data is the first and most important step in machine learning. As a result, an experimental test setup was built in order to collect data on taper roller bearing vibration. The bearing is assembled into a bearing housing and experiments are performed at various speeds. A motor driver is used to control the speed of the motor, and the vibration amplitude is measured using an accelerometer for four different bearing faults and at varying speed conditions. The accelerometer is mounted over the bearing housing. Figure 2 illustrates the experimental setup and components used.

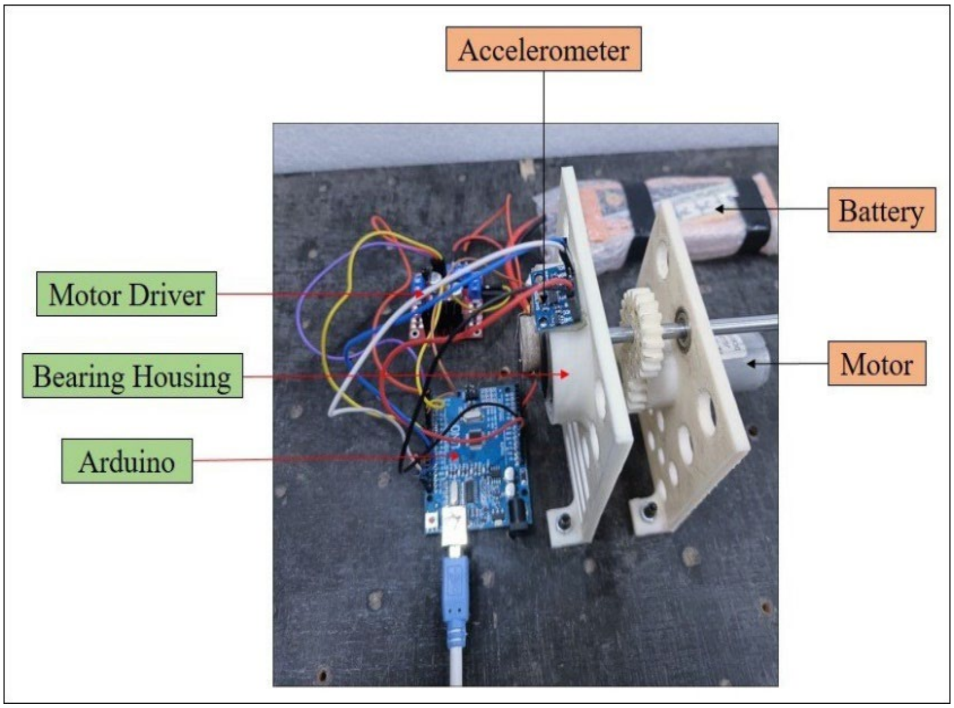
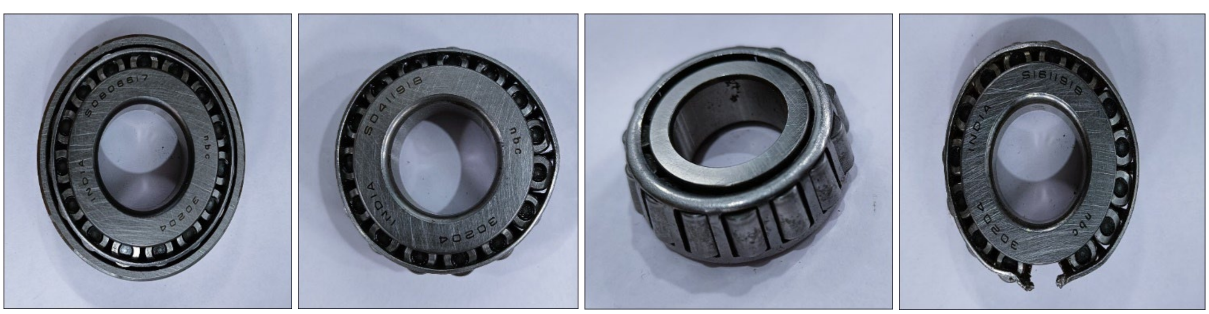


Figure 2. Experimental setup and components used.

In this work, four bearings are used, which are at different operational conditions as shown in Figure 3. Each bearing is then operated at constant speed, increasing speed, increasing and decreasing speed, and decreasing and increasing speed. Bearing specifications are mentioned in Table 1 and Figure 3.



(a) Healthy bearing (b) Cage deform (c) Ball damage (d) Cage and ball defect

Figure 3. Taper roller bearings test conditions

Table 1. Bearing specifications

Name	ID	OD	Width	No. of rollers	Roller Diameter	Pitch Diameter
nbc 30204	20 mm	47 mm	15 mm	15	6 mm	40 mm

5. Data Acquisition

An ADXL 345 accelerometer is used along with the Arduino Uno for collecting the vibration data. The accelerometer is interfaced with the Arduino board and data is collected at a frequency of 400 Hz. Data acquisition is done at constant speed, increasing speed, increasing and decreasing speed, and decreasing and increasing speed combinations with four bearing health conditions such as cage damage, ball damage, cage and ball damage, and no fault. So, four vibration data files are generated with respect to four different speed conditions. In this way, a complete set of sixteen vibration data files is acquired for further study.

6. Results and Discussion

6.1 Data Visualization

Firstly the bearing vibration data is preprocessed and visualized. This is done for each operating speed and with respect to each bearing conditions. The result of data visualization is shown in Figure 4. From this it is clear that the collected data is balanced and unique vibration signal patterns are generated corresponding to different faults at constant speed (Figure 4).

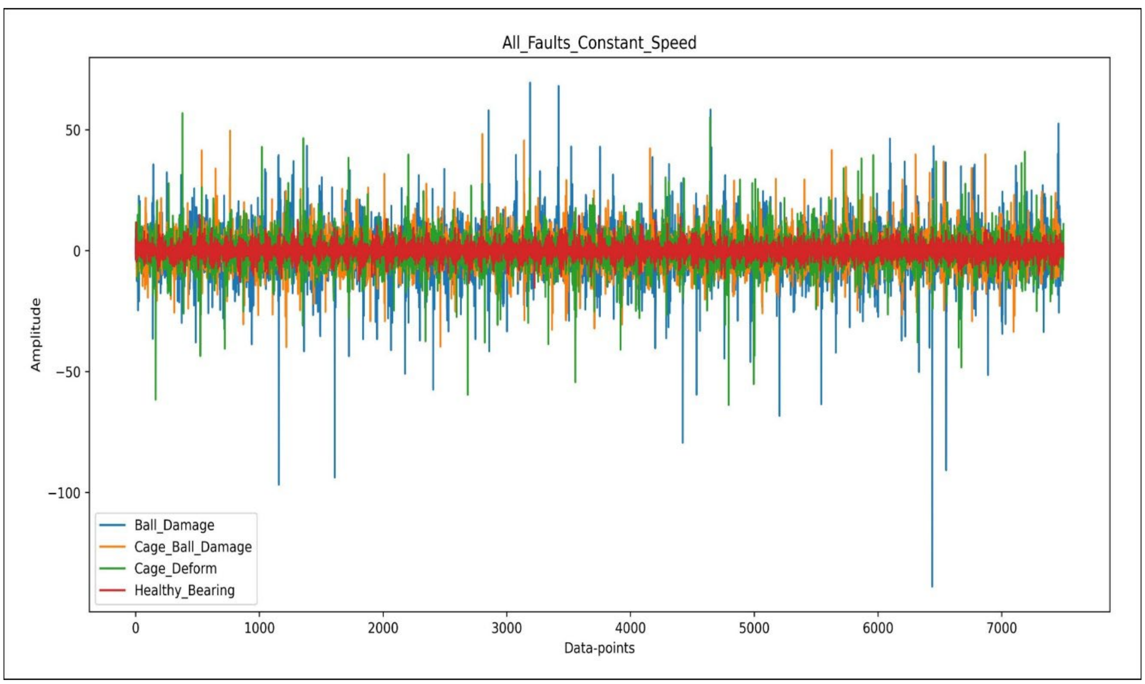


Figure 4. Data visualization

6.2 Feature Extraction

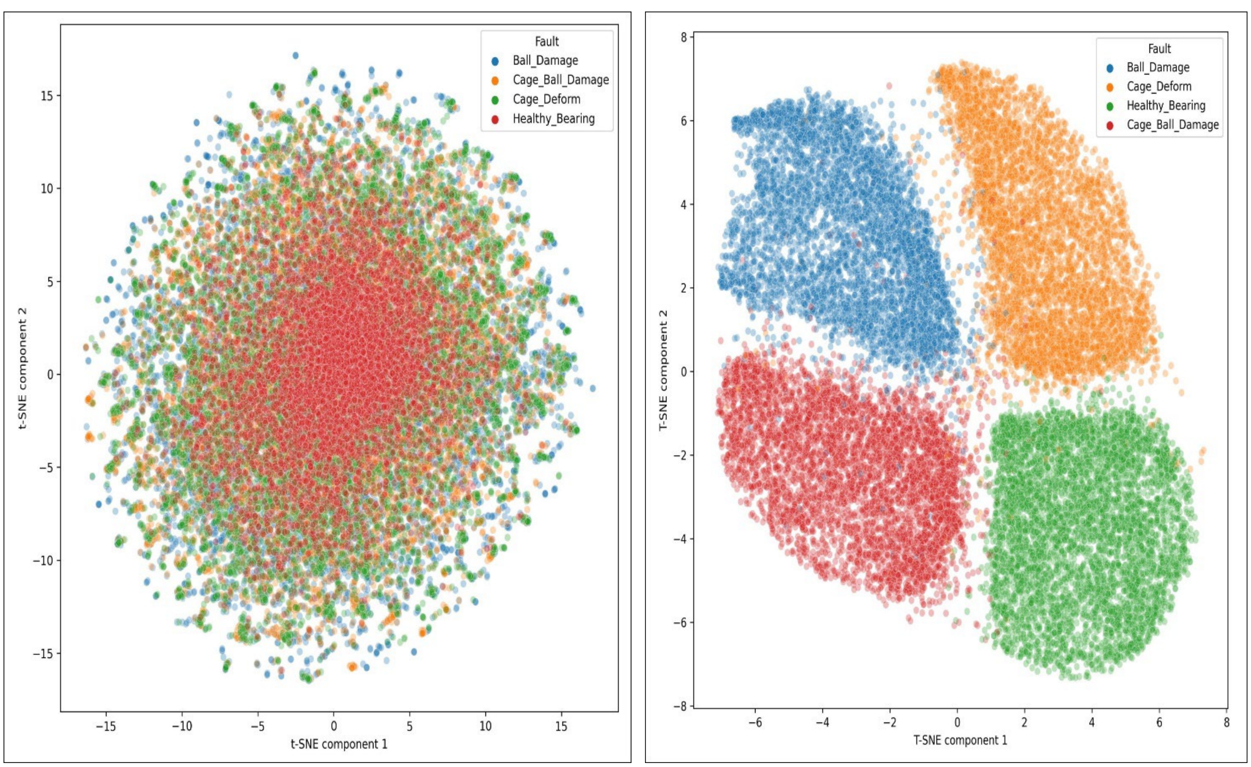
Feature extraction is a technique for converting raw values into statistical feature sets that helps to interpreted bearing condition. It reduces high-dimensional data to low-dimensional data. Table 2 depicts the vibration data feature values for all test cases. This data can be used to classify healthy and faulty bearing conditions.

6.3 Artificial Neural Network (ANN)

The clustering technique used here is TSNE (t-distributed stochastic neighbor embedding). Figure 5 a and b) shows the classification done by model before and after training respectively. It is clearly seen that for constant speed conditions the bearing fault cases are clustered into groups. Similar TSNE plots are obtained for all other operating speeds (Table 2).

Table 2. Feature extraction

Test_Case	Max	Min	Mean	Standard Deviation	Skewness	Kurtosis	Crest Factor	Form Factor
Constant_speed_ball_damage	69.46	-138.84	-0.558233333	9.173792386	-0.924479926	16.48176025	7.558091504	-16.46292
Constant_speed_cage_ball_damage	49.61	-39.83	-0.145133333	6.496621939	0.391794059	5.107691375	7.634880238	-44.77131269
Constant_speed_cage_deform	56.83	-63.76	-0.307128	6.291615023	-0.251506015	12.98038378	9.022514036	-20.50834799
Constant_speed_healthy_bearing	14.78	-15.27	-0.05332	2.865183764	0.110030556	1.789642044	5.157933142	-53.74135162
Inc_Speed_ball_damage	71.03	-96.31	-0.422094667	8.795292865	-0.325137209	8.071839164	8.067163403	-20.85984592
Inc_Speed_cage_ball_damage	62.32	-54.97	-0.440797333	6.346739076	0.400047474	10.80208932	9.796268732	-14.43204239
Inc_Speed_cage_deform	49.06	-67.13	-0.264762667	5.792854898	-0.052178458	11.71949568	8.460784848	-21.90080841
Inc_Speed_healthy_bearing	14.85	-14.72	-0.019509333	2.503552148	0.139370502	2.272380491	5.931787423	-128.3212099
inc_dec_speed_ball_damage	129.32	-70.35	-0.298468	8.519682408	0.561664978	14.29285999	15.17067377	-28.56031881
inc_dec_speed_cage_ball_damage	61.06	-34.89	-0.23094	6.096002821	0.703545623	9.31801404	10.00988599	-26.4136554
inc_dec_speed_cage_deform	67.65	-51.99	-0.302348	6.146325889	0.31403391	10.75518728	10.99401385	-20.35187473
inc_dec_speed_healthy_bearing	21.76	-15.98	-0.052122667	2.810252385	0.112057852	2.817966679	7.742261295	-53.9218073
dec_inc_speed_ball_damage	76.99	-92.39	-0.023973333	8.308102613	0.077627343	11.96566392	9.267436403	-346.5343428
dec_inc_speed_cage_ball_damage	61.06	-34.89	-0.23094	6.096002821	0.703545623	9.31801404	10.00988599	-26.4136554
dec_inc_speed_cage_deform	63.42	-46.73	-0.256065333	5.830343634	0.34508331	9.021769409	10.86782231	-22.7894016
dec_inc_speed_healthy_bearing	21.37	-15.35	-0.049049333	2.778174455	0.08734972	2.637550831	7.691415594	-56.64546351



5 (a) Clustering on data before training

5 (b) Clustering on data after training

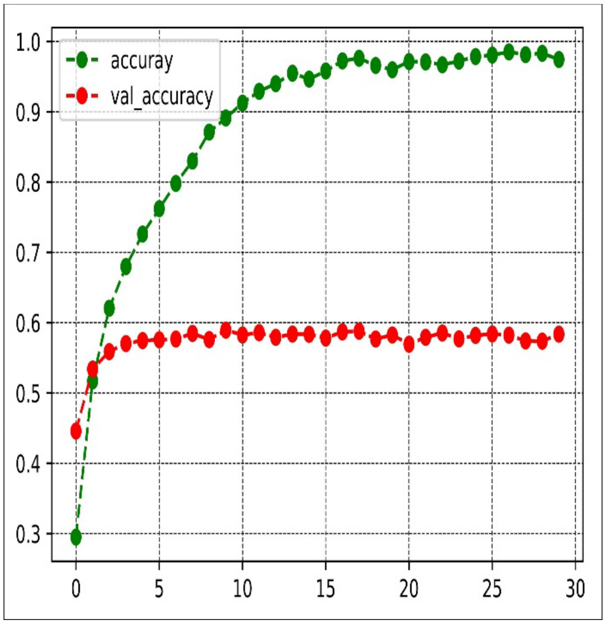


Figure 6. ANN training and validation graph

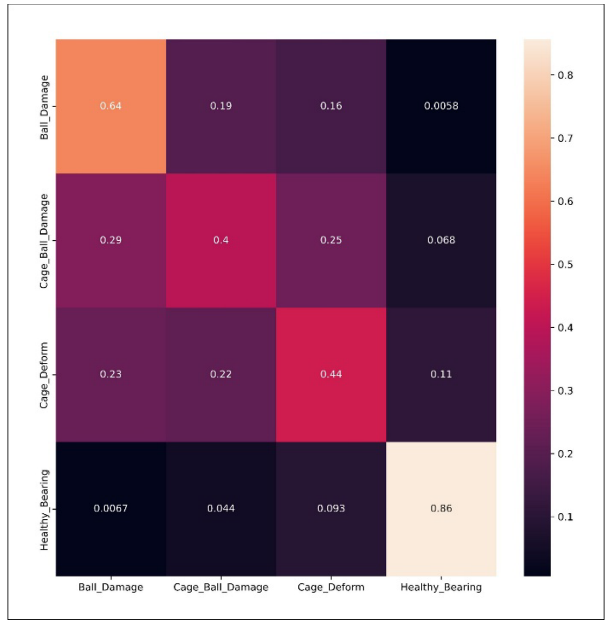


Figure 7. ANN confusion matrix

Figure 6 is the training and validation accuracy graph of the model at constant speed which shows the validation accuracy achieved is 58%. The confusion matrix generated for constant speed condition using ANN is also shown in Figure 7. Similarly, ANN training and validation graphs and confusion matrices are obtained for all other speeds and fault conditions.

6.4 One Dimensional Convolutional Neural Network (1D CNN)

All results for constant speed obtained from 1D CNN are shown in the below Figures. Training and validation curve in Figure 8 is important to investigate because it shows how the model learns and then how accurately it is practiced. The green colour follows the training accuracy, and the red coloured plot follows the validation accuracy. Figure 9 shows the fault clustering done and from the plot, it is clear that the ML model is able to diagnose the type of fault in bearing. A confusion matrix in Figure 10 is used for evaluating the performance of an ML model by comparing actual values with those predicted. From which it is inferred that whether a bearing is faulty or healthy, it is diagnosed with 99% accuracy, but while diagnosing the type of fault an accuracy range is 94% to 97%. Similarly, results for all other speed conditions are studied in this paper.

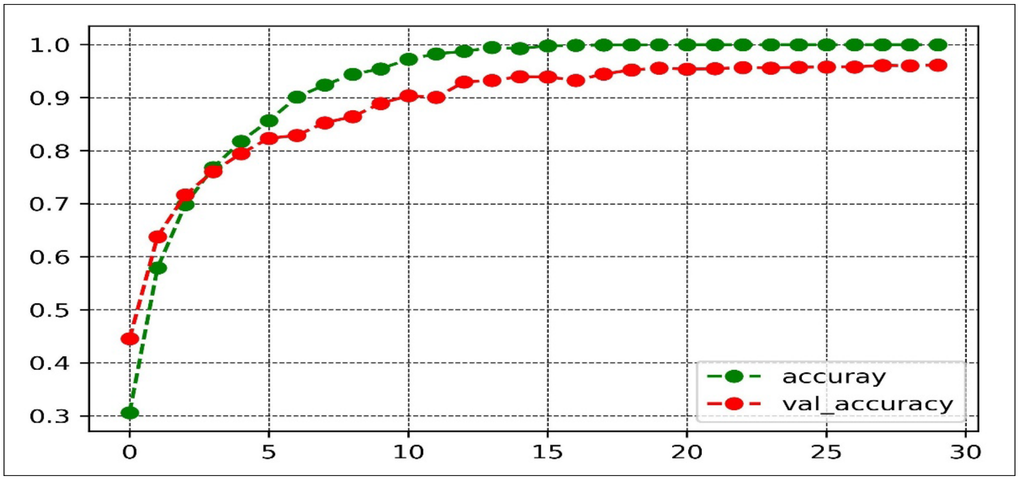


Figure 8. 1D CNN training and validation graph

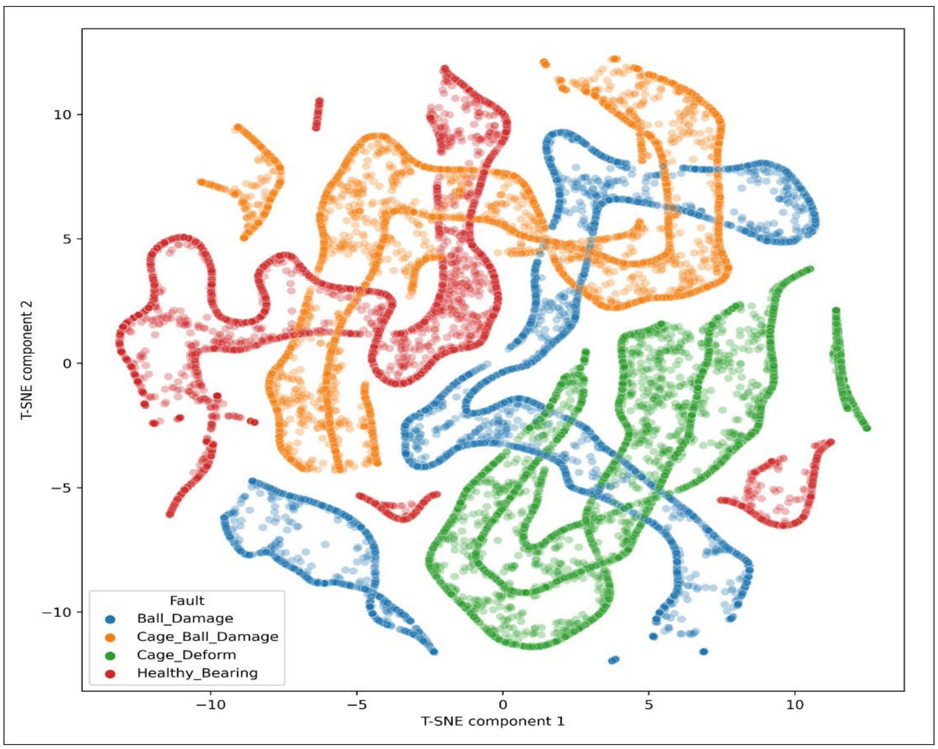


Figure 9. Fault clustering using 1D CNN

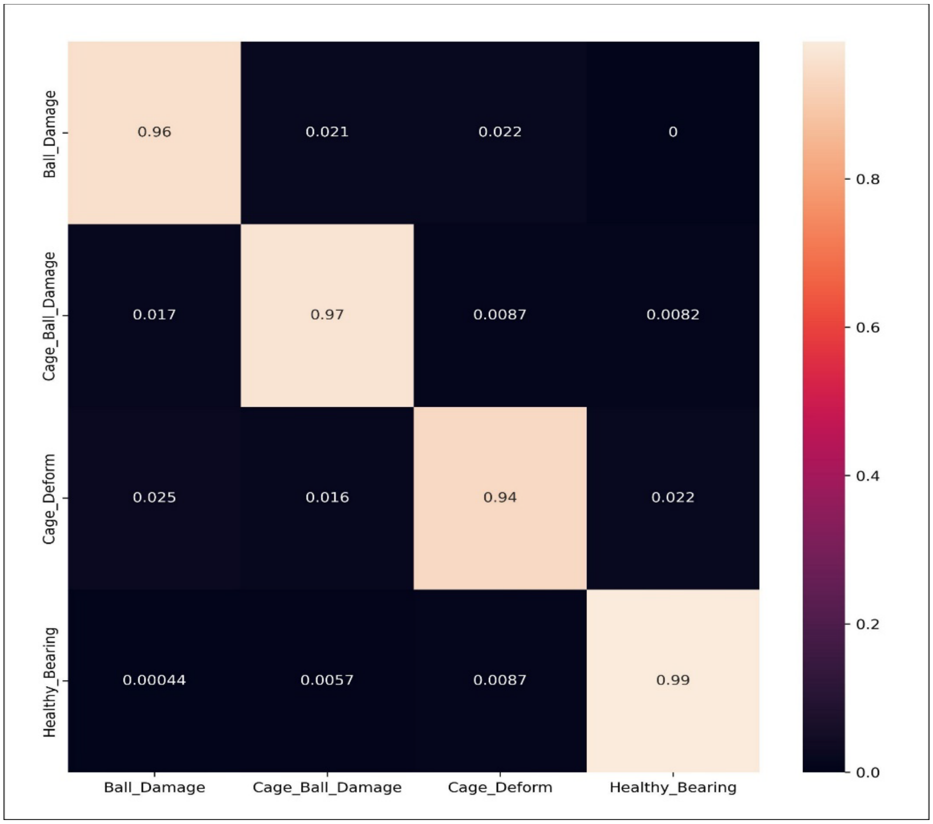
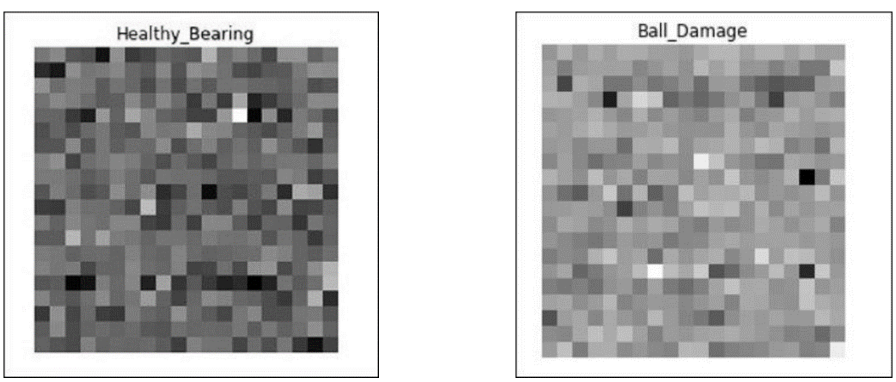


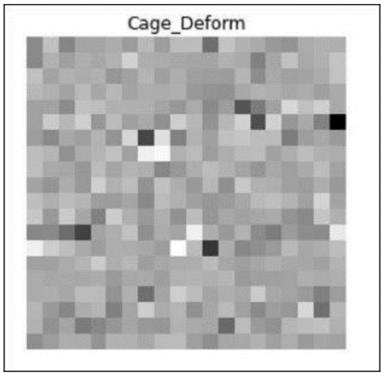
Figure 10. 1D CNN confusion matrix

6.5 Two Dimensional Convolutional Neural Network (2D CNN)

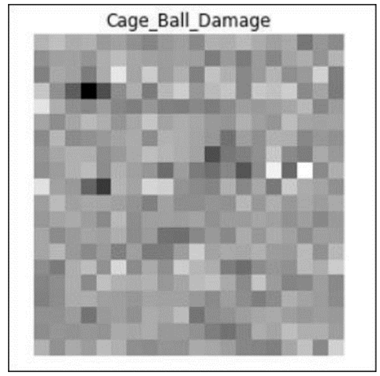
A CNN learns the features from 2D image input more efficiently than a 1D signal. In this section, greyscale vibration images are generated from 1D vibration signals. A window length of 400 data points is created to transform the vibration into 20x20 pixel image. CNN learns through extracting features from these images. For constant speed a total of 5680 vibration images are generated, out of which 70% (3976) images are used for training and remaining 30% (1704) images for validation.



(a) Healthy (b) Ball damage



(c) Cage deform



(d) Cage and ball defect

Figure 11. Vibration images for all test cases

Figure 11 shows the vibration images generated form corresponding bearing signal. These are the gray scale images which has pixcel value ranging from 0 to 255. Generally, zero is considered black, and 255 is considered as white pixcel. Total 22,720 vibration images generated from all each bearing fault conditions and operating speeds.

6.5.1 Hyperparameters of 2D CNN

The total number of training and testing images for each dataset is 3976 and 1704, respectively. Because vibration data is not very complex, the depth of two convolution layer (CL) and two pooling layers (PL) is sufficient to generate feature maps. Table 3 shows the detailed structure of the CNN model (Table 3).

Table 3. CNN parameters

Layer	Kernel Size	Kernel Number	Padding Type	Activation Function	Output Size
CL1	3 x 3	20	Same	Relu	20 x 20x 20
PL1	2 x 2	20	Same	-	10 x 10x 20
CL2	3 x 3	40	Same	Relu	10 x 10x 40
PL2	2 x 2	40	Same	-	5 x5 x 40

From the structure of CNN, it is clear that the flatten layer has a continuous linear vector of 1000 units. This vector is then passed into the fully connected dense layer and finally, softmax activation function is used to perform fault diagnostics. As explained in 1D CNN Figure 12 shows the t-sne plot w.r.t to bearing fault conditions at constant speed. Training and validation curve is also given in Figure 13 which indicate the validation accuracy achieved is upto 99%. The classification results from confusion matrices in Figure 14 indicate that the accuracy in detecting whether bearing is faulty or not is 100% and for diagnosing the type of fault an average accuracy range is 98%. Similarly, results for all other speed conditions are studied in this work.

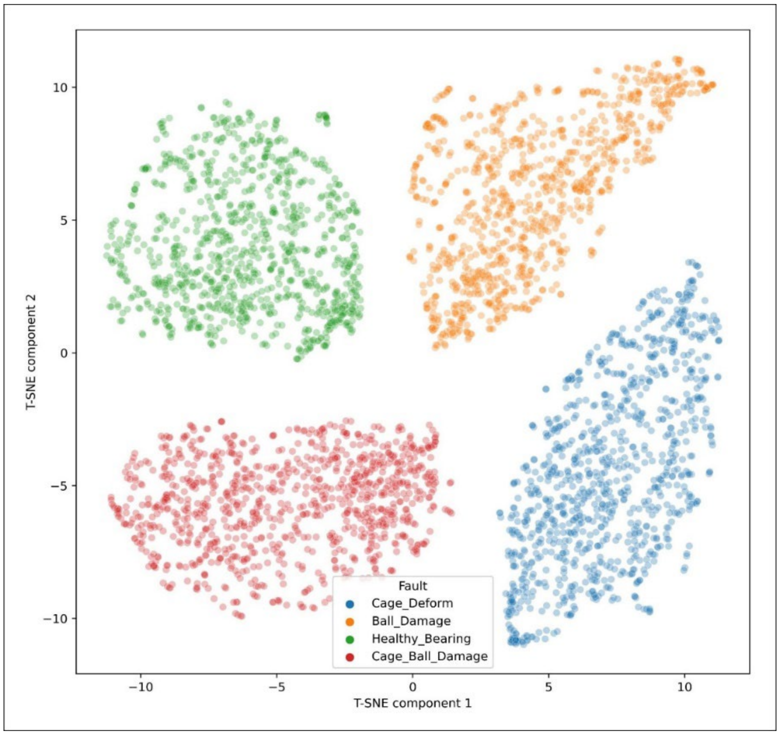


Figure 12. Fault clustering using 2D CNN

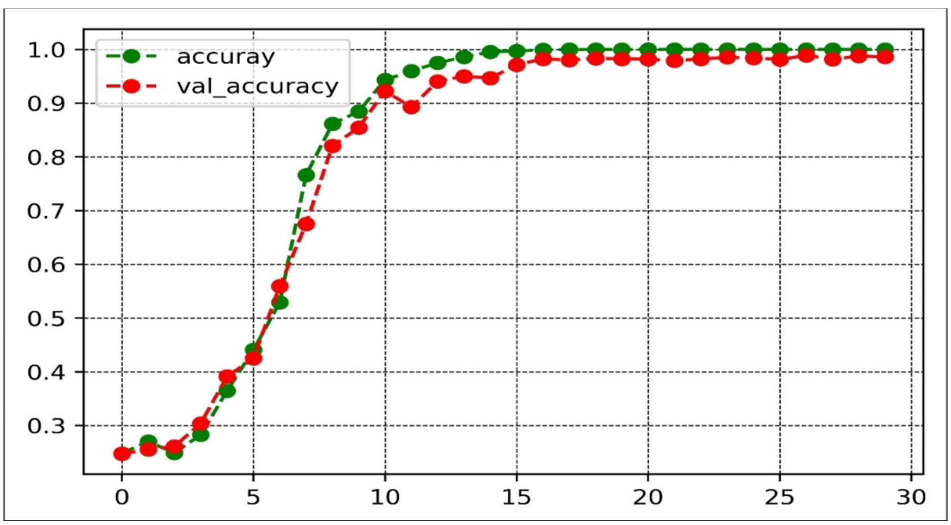


Figure 13. 2D CNN training and validation graph

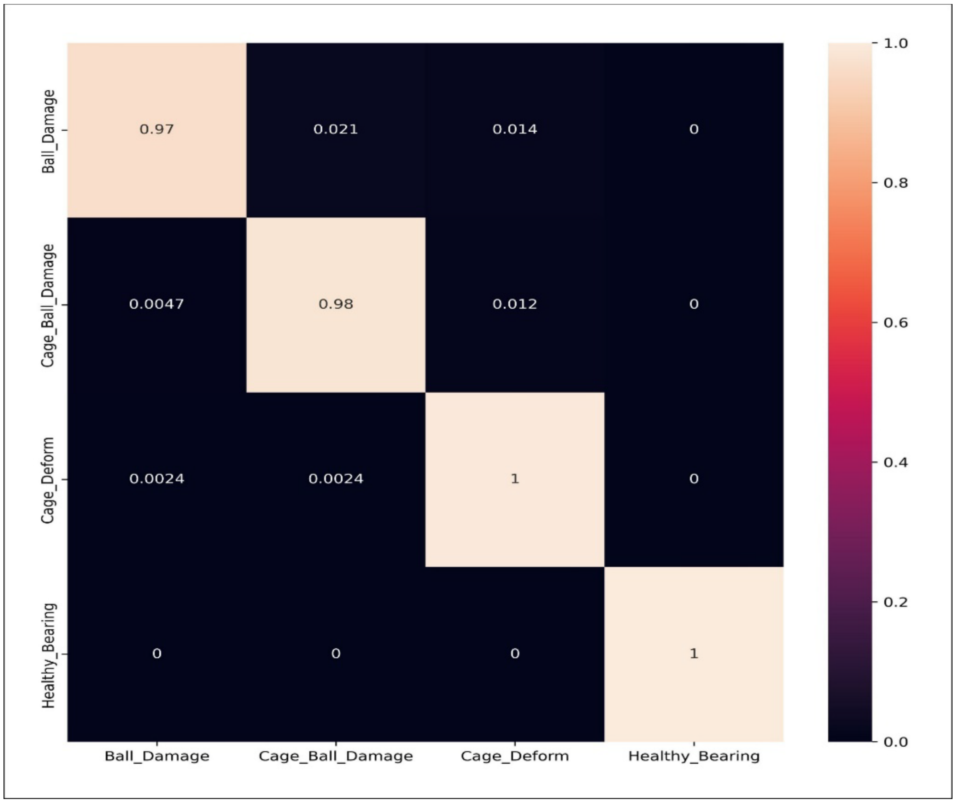


Figure 14. 2D CNN confusion matrix

7. Conclusion

a) According to feature extraction and data visualization studies, faulty bearings generate more vibrations, and the vibration spectrum differs significantly and uniquely between healthy and faulty conditions.
b) The developed data acquisition unit is able to sense and capture the unique pattern in vibration signals.
c) The new approach based on CNN is developed in this study for diagnosing faults in the time domain vibration signals of taper roller bearings by 2-D image generation from vibration signals and utilizing CNN effectively for classification of images.
d) Comparative study of fault diagnosis using ANN, 1D CNN, and 2D CNN is done on the same bearing data set. This shows that ANN gives only 55% accuracy, whereas both CNN-based approaches, are able to do fault diagnosis with 99% accuracy.
e) The robustness of the model is tested by carrying out the experiments at varying speeds of bearing and also with combined faults. Under such varying operating conditions the deviation in validation accuracy score is only 1%. Hence above methods proved to be automatic, fast, and reliable to implement in industries.

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Biographies

Mahesh S. Bankar is a graduate in Mechanical Engineering from Government College of Engineering, Aurangabad, and pursuing a master's degree in Mechatronics Engineering from College of Engineering, Pune.

Dr. B. B. Ahuja is a senior faculty at the Department of Manufacturing Engineering and Industrial Management, College of Engineering, Pune.

Dr. Maneetkumar R. Dhanvijay is working as faculty in the Department of Manufacturing Engineering and Industrial Management, College of Engineering, Pune since 2013. Prior to that he has worked with the Department of Mechanical Engineering of two other colleges. His research interests are Mechatronics, Supply Chain Management.