Bearing Various Defects Classification using Deep Network Learning Method

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Diagnostics and classification of faults are critical today, especially in rotating machines, to prevent material and human losses. In order to classify bearing faults, this paper utilizes artificial intelligence methods, namely deep network learning. This field has used a variety of methods to detect and predict bearing faults, but none of them are foolproof or perfect. There are many drawbacks to most of these methods, such as the difficulty of extracting vibration signals. As a result of using deep network learning in the present study, the accuracy of the results has been improved compared to the previous methods. The results have showed that the proposed technique is superior to the previously studied method and can be used to classify induction motor bearing faults effectively.

Keywords: Rotating machines, Fault diagnosis, Bearing defects, Deep network learning, Faults classification.

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1 Introduction

Increasing industrial production means an effective system of monitoring process is required in order to eliminate machine failures, rise machine availability and significantly reduce maintenance operating costs [1]. Induction machines are more likely to fail, according to the IEEE Industry Application Society (IEEE-IAS) [2] [3] and the Japan Society for the Promotion of Science and Technology (JSPS). A bearing problem is the most prevalent sort of electrical defect, according to the Electrical Manufacturers Association (JEMA) [4]. Bearing issues are estimated at 30 to 40% of most machines breakdowns. Many methods for analyzing vibratory signals have been developed, including Wavelet Transform approaches classified into three types: continuous wavelet transform (CWT) [1, 5], discrete wavelet transform (DWT) [1], and wavelet packet transform (WPT) [6], however none of them is ideal. Every approach has benefits and drawbacks.

Network characteristics are acquired straightly and in adaptive manner from input data. Employing Deep Learning Network with Parallel Convolution Layers and Multi-Scale Kernels, wind turbines intelligent fault diagnosis is possible.

In [11] the author reviews the previously published works on bearing defect diagnosis with deep learning techniques. Although usual machine learning techniques, as well as artificial neural network, main component analysis and support vector machines were effectively applied and used for bearing defects detection and categorization. Another survey [12] based on Models with multiple processing layers, which can learn representations for data at multiple abstraction levels through deep learning.

When induction motor bearings fail, the Stock well Transform is used to detect the failure. It is possible to classify bearing defects in an induction motor using a convolutional neural network [13].

In this work, six bearing faults are studied (normal or healthy bearing, bearing with outer race fault, inner race fault, ball fault, un-lubricated bearing and un-lubricated bearing with ball fault). Bearing vibration signal analysis is conducted by deep network learning method.

2 Deep Network Learning Theoretical Development

Deep learning concept

Deep learning is a kind of artificial intelligence (AI) and system learning that mimic the way humans obtain knowledge. It is very important for data scientists responsible for collecting, examining and explain big quantities of data, with deep learning this procedure will be not difficult and will require less time.

The idea of deep learning is previously introduced. It becomes an interesting subject these days because of the availability of more processing power and a large amount data. While in recent two decays, the processing power has increased intensively, deep learning and machine learning became a timely topic. A deep neural network is just a shallow neural network with several hidden layers. Every neuron in the hidden layer is linked to several other layers. Each arrow has a weight feature that governs how much the startup of one neuron impacts the others related to it.

Deep refers to these deep hidden layers, and its efficiency stems from them. The hidden layer number used is governed by the nature of the issue and the volume of data collected. Figure (1), illustrates two hidden layers deep neural network.

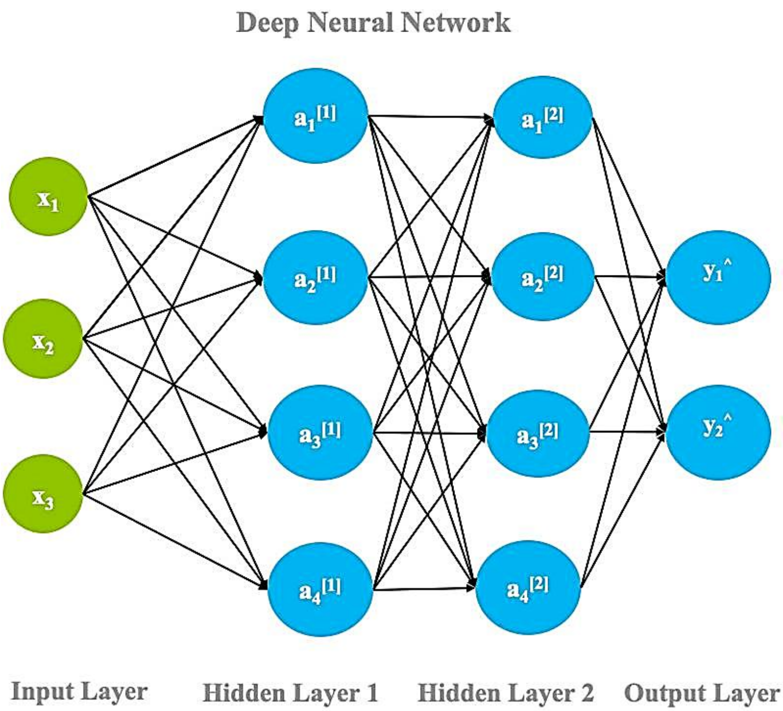


Fig. 1. Two hidden layers deep neural network

How Do Deep Learning algorithms "learn"

Deep Learning Algorithms utilize a neural network to get relations between a set of inputs and outputs. The main architecture is illustrated in figure (2).

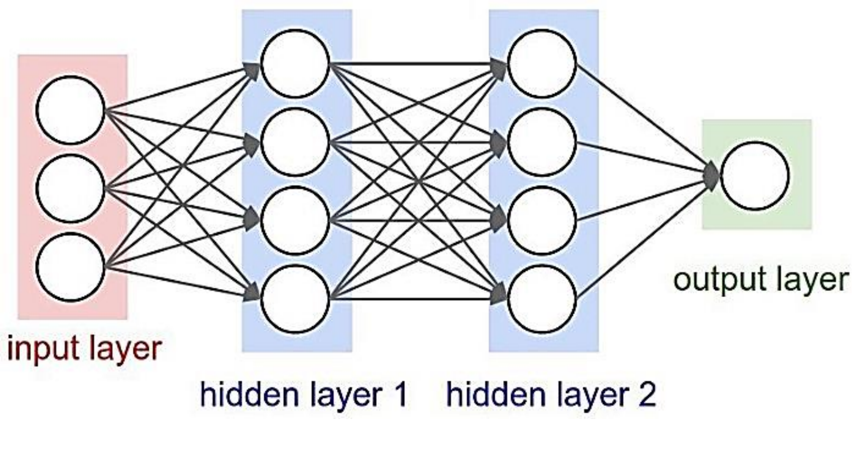


Fig. 2. The basic structure of a neural network

A neural network is made up of input, hidden, and output layers, which are all designed from “nodes," as presented in figure (3). Input layers receive a numerical illustration of input (for example, photos with pixel specifications); output layers provide predictions; and hidden layers are connected with the majority of calculation.

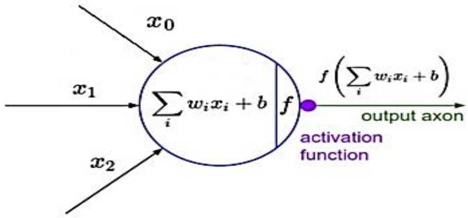


Fig. 3. Node representation

The above code is used to move data between network layers. The changeable weight and bias parameters, which are denoted by w and b in the expression above, are the most important things to understand. These are necessary for the actual "learning" phase of a deep learning algorithm.

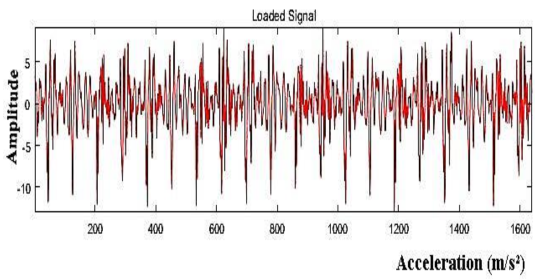
Next to this when the neural network has processed all its inputs and outputs, and then the prediction evaluation starts by using a loss function. An example of Mean Squared Error loss function is presented below.

$$\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y_i})^2$$

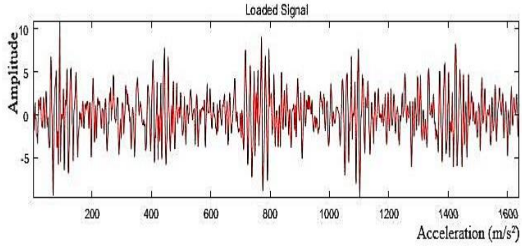
Y hat denotes the prediction and **Y** is the expected output. An average is employed if a several inputs and outputs are used at the same time (**n** denotes sample count).

3 Data Acquisition

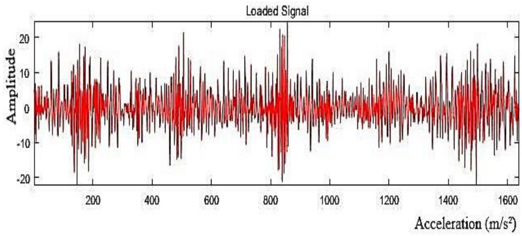
The vibratory signal is obtained using the test rig indicated in figure (4). The observed vibration signals are produced by the experimental setup shaft, which is powered by an induction motor via a connection, a bearing unit, and a flywheel as a driven mechanism. This is composed from a PC to visualize and record the vibratory signals, an induction motor of 0.37 KW, a USB measuring device, a sensor, a bearing unit, and a mechanism. As shown in figure (4) the vibration sensor employed in this investigation measures the vibration produced by six bearing states (healthy bearing, bearing with outer race fault, bearing with inner race fault, bearing with ball fault, un-lubricated bearing and un-lubricated bearing with ball fault).



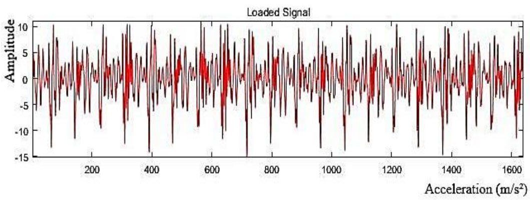
a) Healthy bearing signal



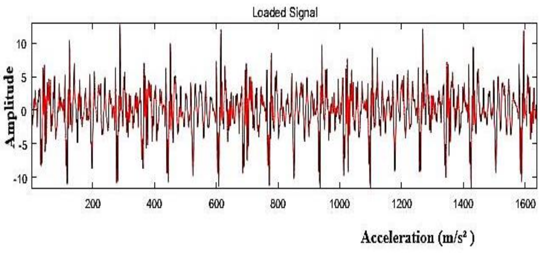
b) Bearing with outer race fault signal



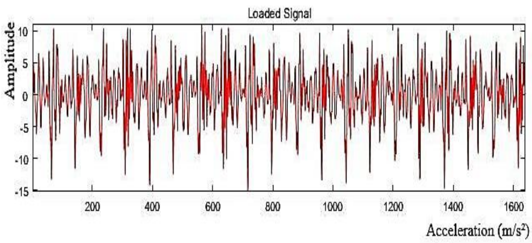
c) Bearing with inner race fault signal



d) Bearing with ball fault signal



e) Un-lubricated bearing signal



f) Un-lubricated bearing with ball fault signal. **Fig .4.** Different bearing faults vibratory signals

In a series of tests, vibration signals are measured and recorded at 1000 rpm rotational speed. While operating, there are a variety of stresses that can be placed on the coating. Many samples are then extracted from every case and entered into MATLAB to be processed with the deep network learning method, in order to create a model that may subsequently be used to categorize signals.

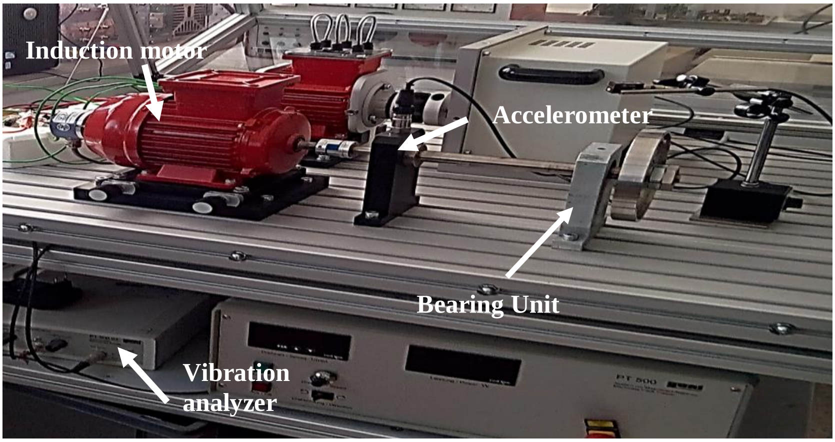


Fig. 5. Data acquisition setup

4 Results and Discussions

The model of simulation is built using the deep network designer as it illustrated in figure (6).

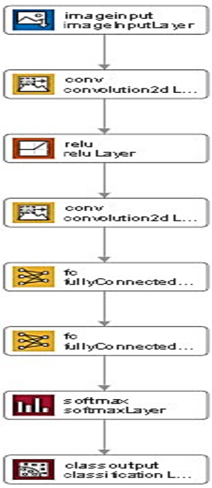


Fig. 6. Deep network learning classification for bearing faults

It must be imported (uploaded) all the data into MATLAB program for each of the previous classes (healthy bearing, bearing with outer race, inner race, ball defects, un-lubricated bearing and un-lubricated bearing with ball fault) at low rotational speed of 1000 rpm as shown in figure (7).

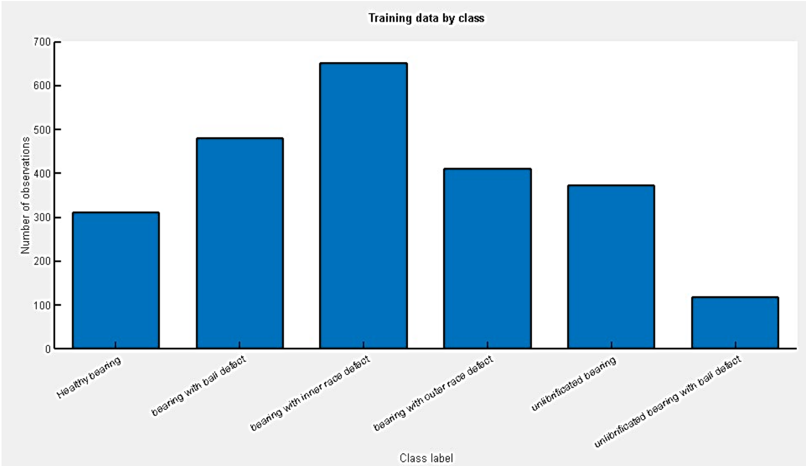


Fig. 7. Deep network learning classification for bearing defects

The final step is training the model to get the accuracy (%) as presented in figure (8). After obtaining a reliable model with a high accuracy (83%), the different vibratory signals can be classified at a rotational speed of 1000 rpm. All the results are shown in Table.1.

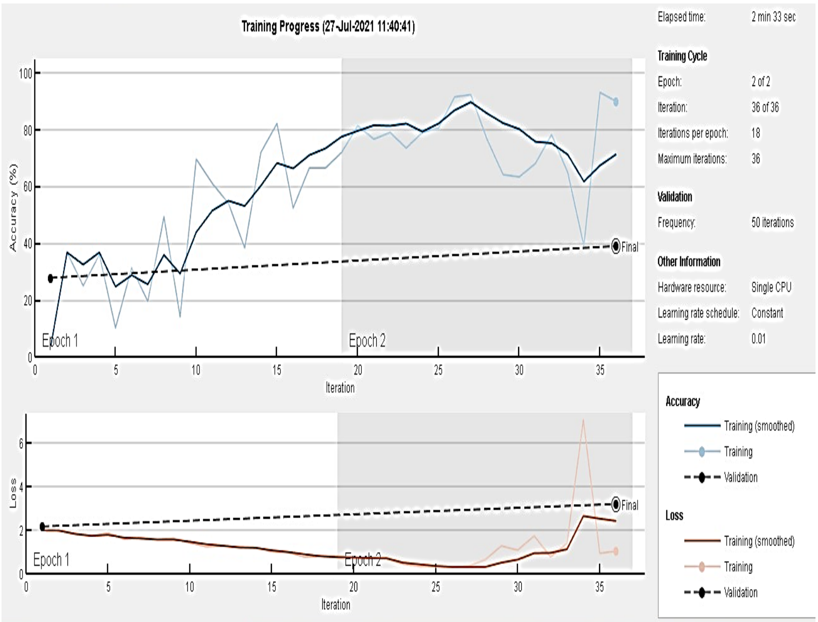


Fig. 8. Deep network learning classification for bearing defects

After classification and obtaining different classes as illustrated in figure (7), it must be uploaded for different vibratory signal representations to test and gets the final class for each representation for different cases of rotational speed (1000 rpm) using the deep network learning technique. The obtained results are summarized in table.1.

Table 1. Bearing faults classification for a rotational speed of 1000 rpm

Bearing defect type	Healthy class (%)	Inner class (%)	Outer class (%)	Ball defect class (%)	Un-lubricated bearing class (%)	Un-lubricated bearing with ball defect class (%)	Final defect classification according to (%) of each class
Healthy bearing	90%	5%	0%	5%	0%	0%	Healthy
Inner race bearing	0%	98%	0%	0%	1%	1%	Inner
Outer race bearing	2%	6%	84%	2%	4%	2%	Outer
Ball Bearing defect	16%	12%	0%	50%	10%	12%	Ball defect
Un-lubricated bearing	5%	20%	13%	10%	32%	20%	Un-lubricated bearing
Un-lubricated bearing with ball defect	2%	5%	11%	12%	30%	40%	Un-lubricated bearing with ball defect

In the first case, the vibratory signals of a healthy bearing and different cases of faults at a rotational speed of 1000 rpm were analyzed employing deep network learning. According to Table.1, the highest percentage is 90%, corresponding to the case of a healthy bearing. In the second case, the highest percentage is 98%, corresponding to an inner race fault. In the third case, the highest percentage is 84%, corresponding to a bearing outer race fault. In the fourth case, the highest percentage is 50%, corresponding to a ball fault. The next case, the highest value was 32%, corresponding to un-lubricated bearing fault. In the final test, the maximum value was 40%, which was attributed to un-lubricated bearing with a ball defect. It can be summarized that the deep network learning technique is an effective and precise tool for faults classification.

5 Conclusion

In recent years, rotating equipment monitoring and diagnosis has grown more successful as a result of vibration analysis. In order to improve monitoring systems, a variety of methods are used to analyze vibrational signals. Vibration analysis has several advantages over other methodologies. In the present work a deep network learning method is applied for the classification of induction motor various bearing defects. The obtained results have demonstrated the effectiveness and the precision of this technique which can be extended to others rotating machines faults.

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