Defect Diagnosis of Rolling Element Bearing using Deep Learning

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***Abstract*— The bearing element is an important part of many mechanical facilities. This element is very important for the maintenance of the machine and for the detection of machine faults. The presence of a rolling fault in the machines can affect the overall performance of the machine. For this reason, the bearing faults must be diagnosed in order to be monitored for the machine in a healthy manner. The generated vibration signals as a result of the machine's rolling action should be monitored in order to diagnosis the machine defects. It is assumed that the vibration signals are composed of large-scale features and noise components. The performance of traditional diagnostic methods is based on characterizing faulty vibration signals. The utility of traditional techniques requires signal processing, expert knowledge, and human effort. In the most basic sense, the diagnosis of defective vibration signals is based on a comparison of defective vibration signals to healthy signals. In this study, deep learning technology which has been applied to many fields in recent years has been used to detect defective vibration signals. The ability to learn the complex features of the deep learning architecture provides superiority over traditional diagnostics to fault diagnosis. In this study, four classes of vibration signals have been used as input data. Training and test data for each class have been created. These images have been then trained on the CNN model that has been developed in Keras deep learning library. This model has been developed to automatically diagnose vibration signals. The developed model produced results with high accuracy.**

***Keywords*— Rolling element, Bearing, Vibration signal, Classification, Deep learning, Fault diagnosis, Keras.**

I. INTRODUCTION

Today, most of the machines used in the industry are doing business with the rolling action. It is necessary to eliminate the fault by determining and maintaining it at the initial stage of the failures that occur because these machines can do without disrupting the task. The vibration is the most suitable way to do this. It is easy to identify faults if the vibrations caused by failures in rolling machines are well understood. The proper functioning of the machines is closely related to the healthy operation of the bearings. The increment in the clearance between working parts, wear on parts, cracks, etc. causes cause vibrations [1]. Even a properly manufactured machine generates vibration at a certain level during operation. One of the most important causes of failures arising from failures in rolling machines is bearing failures. There is a need for knowledge and experience in determining the fault source by measuring the vibration of the machine. The possible problems coming from the assembly of the machine coming from its manufacture make it difficult to determine the source of the fault. For this reason, the determination of machine malfunctions is in the form of a comparison of the graphs taken at certain intervals. The change in the graphs occurs at fault frequencies. The signals due to faulty signals can be distinguished by comparing them with each other. The comparison can be done using FFT spectrum, waveform graphs, and trends [2]. The basic working principle in predictive maintenance methods is to determine the time of maintenance by monitoring the performances of the machines with the measurements made during the operation and to repair the defects determined [3].

Failures occurring in bearings can be classified as regional and scattered [4-6]. Rolling elements in bearings generate short-duration, damped signals in Fig. 1 as they pass over the damage [7, 8]. It is necessary to examine the vibration frequencies to determine which element of the bearing the damage originates from. It is necessary to examine the vibration frequencies to determine which element of the bearing the damage originates from. the inner ring rolling outer ring can be calculated based on the vibrational frequencies of the elements of a fixed bearing, the bearing geometry, and a pivoting revolution [9]. The frequencies obtained as a result of these calculations are compared with the frequencies obtained as the result of the measurement. Many studies have been carried out in the literature regarding the diagnosis and analysis of vibration failure signals in bearings.

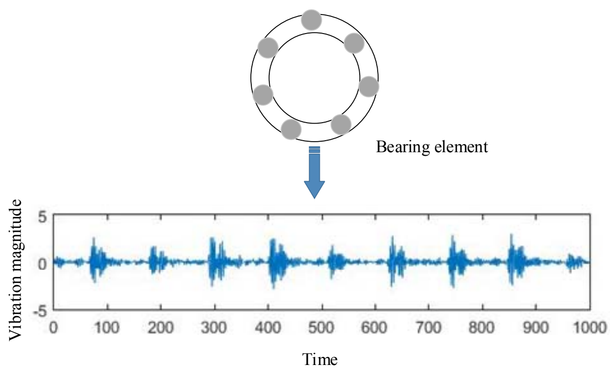

Fig. 1. An example of faulty vibration signals of the bearing

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Ying et al. [10] an approach based on dualentropy, holder coefficient and gray relation theory proposed to analysis rolling bearing vibration signal. Dybala [11] recommended the diagnostic method allowing early detection of a rolling-element bearing fault at the low-energy stage of its improvement. This method maintained automatic method of amplitude level-based signal decomposition. Zhang and Huang [12] presented a method that used particle swarm optimization and RBF neural network to fault diagnosis of rolling bearing. Merainani et al. [13] proposed the empirical wavelet transform (EWT) method for the vibration signal analysis and fault diagnosis of rolling bearing.

Abdelkader et al. [14] recommended a threshold de-noising method based on Empirical Mode Decomposition (EMD). Zilong and Wei [15] developed a novel deep convolutional neural networks to manage on the raw vibration signal. Zhang et al. [16] suggested a fault diagnosis to classify of vibration signals with different fault location and different damage degree. In [16] study, Deep Fully Convolutional Neural Network (DFCNN) was utilized to train the data set. Sun et al. [17] developed a method that is inspired by the idea of compressed sensing and deep learning. The proposed method [17] reduces the need for human labor and expertise and presents a new procedure to handle the extensive data more easily. Hoang and Kang proposed a method for diagnosing bearing faults based on a deep structure of the convolutional neural network.

In this study, a method is proposed for diagnosing whether the vibration signals generated by the rotating machines are defective or not. The vibration signals obtained as a result of the machine's rotational motion are recorded. These recorded signals are then divided into the designated number of segments to form a training value of each segment value and the signal is improved by applying preprocessing on the obtained signal data and then the signal data have been trained in the developed Convolutional Neural Network (CNN) model. In this study, there are four classes in the training set. The developed deep learning model ultimately classifies the signal data into four categories. The proposed method has been tested with test data and results have been obtained with high accuracy.

II. The Proposed Method

The CNN model of deep learning architecture is frequently used in image classification applications. The vibration signals obtained in this study are firstly recorded as images. The signal recorded as the image is passed through the preprocessing step to improve the signal. The signal obtained as a result of preprocessing is segmented by a certain number of bands. The signal data in this study is 400 pixels wide and divided into 100 segments. Each of the segments constitutes the data of the training set. The signal belonging to four different categories is used in the signal data. This signal data has been trained in the later developed CNN model and feature extraction has been made with a Softmax function to identify the type of vibration failure [19-21]. The signal types used in this study are normal, ball, inner race and outer race. Fig. 2 indicates the basic block diagram of the proposed method.

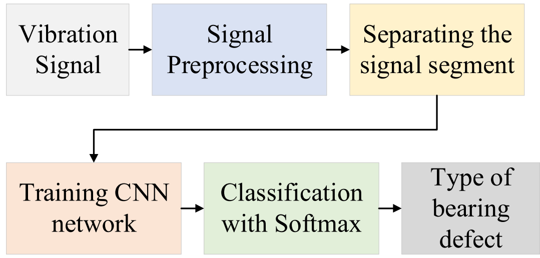


Fig. 2. The block diagram of proposed method

The preprocessing step of the vibration images has improved the signal and normalized it. It is aimed to increase the accurate rate of the images during training. The signal obtained as a result of the signal preprocessing is given in Fig. 3.

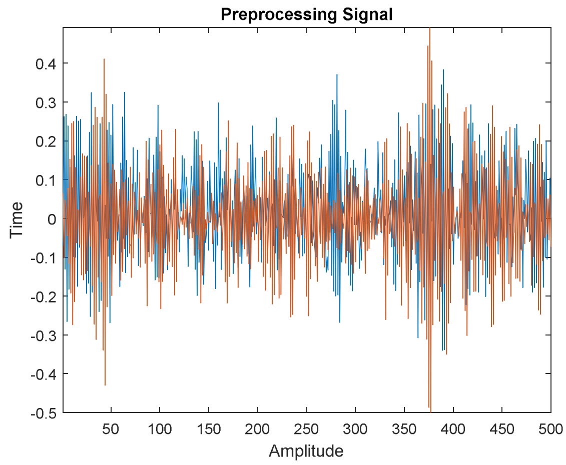


Fig. 3. Signal preprocessing

The signal images obtained as a result of preprocessing are divided into 100 segments of 400 pixels in width. Segmenting the signal data is summarized in Fig. 4.

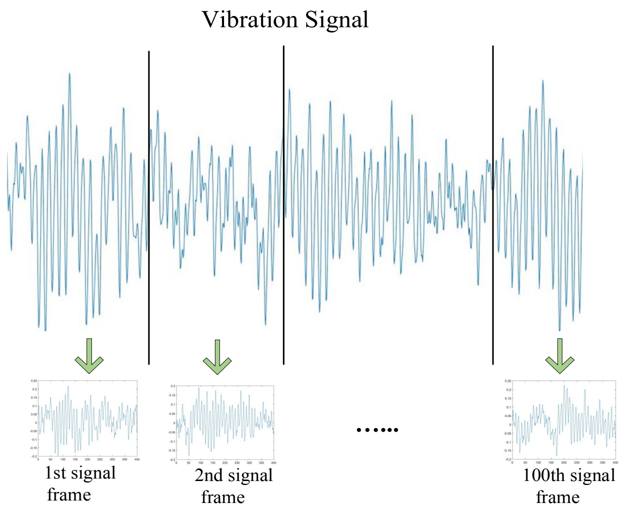


Fig. 4. Segmenting of the vibration signal

Segmented images of vibration signals have been trained with the developed deep learning architecture. CNN architecture has been utilized in the developed model. The developed CNN model is summarized in Fig. 5. This model is convoluted with 32 filters in 3x3 size. Then Pooling is done with 32 filters 2x2 size. Convolution with 64 filters 3x3 size and 64 filters 2x2 size are used for Pooling. Convolution with 128 filters 3x3 size and Pooling is enforced with 128 filters 2x2 size. Convolution with 256 filters 3x3 size and Pooling is enforced with 256 filters 2x2 size. At the last stage Fully connected layer has been classified with Softmax function. The size of the vibration signal images taken as input at the beginning is 128x128 pixels. 70% training data and 30% test data are used in the proposed model. The generated network is trained over 20 iterations. When the model is trained, all the data are not trained at the same time. For this reason, the data is tested by taking the data as specific parts. This situation is reflected to the network developed as back propagation according to success. As the number of iterations increases, network performance increases. However, after a certain value the learning status of the network is greatly reduced.

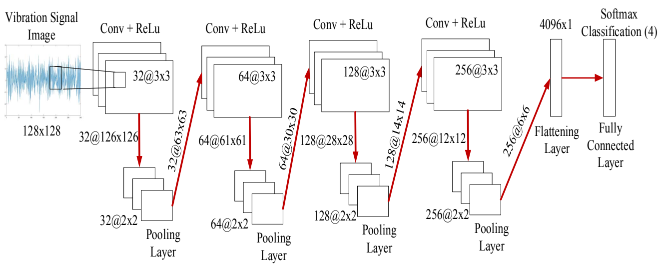


Fig. 5. The proposed CNN model

In this study, the images used for training in the CNN model have been taken from Case Western Reserve University's Bearing Data Center [22]. The process of training takes place with the aid of only CPU. The output of this process would be a classifier which can be utilized to estimate the class of the given input image in prediction phase.

III. Experimental Results

The vibration signals used in this study consist of four categories. These signal classes are normal, ball, inner race and outer race. The bearing machine in which the vibration signals are produced is shown in Fig 6. This experimental setup includes of a two hp motor, a torque transducer, a dynamometer and control electrics. The vibration signals generated by this experimental setup and used in this study are given in Fig. 7.

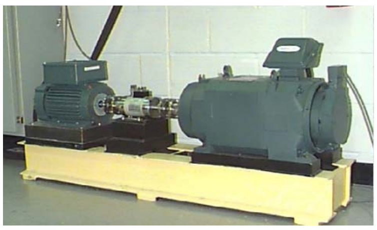


Fig. 6. Experimental setup for vibration signal

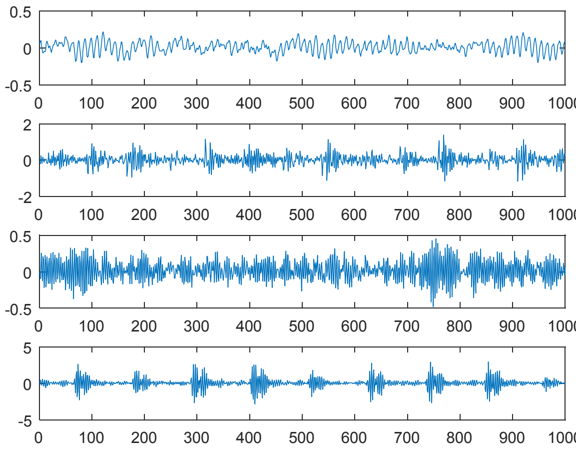
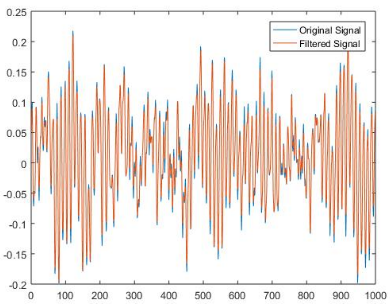
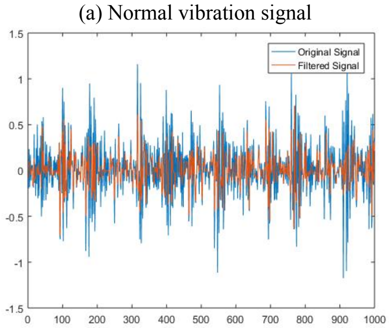


Fig. 7. The vibration signals used in proposed method

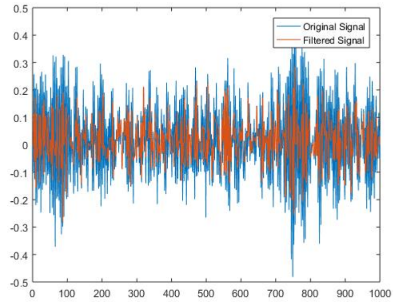
Each vibration signal is normalized by applying pre-processing to the vibration signals generated by the bearing machines. The vibration signals for each category are divided into 100 segments. Training has been carried out on the proposed CNN model using images in each category segmented. The proposed CNN model has been implemented in the Ubuntu operating system using the Python programming language. OpenCV has been used to read images from the database and Keras, a deep learning library, has been utilized. Other libraries used in the Python programming language are Matplotlib, Numpy, Scipy and PIL. The images obtained by passing a sample vibration signal through the recommended network layers are given in Fig. 9. The confusion matrix obtained as a result of the test images is shown in Fig. 10. The classification performance measures obtained in this study have been calculated.



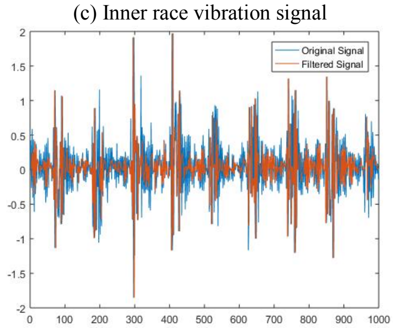
(a) Normal vibration signal



(b) Ball vibration signal



(c) Inner race vibration signal



(d) Outer race vibration signal

Fig. 8. Preprocessing signals

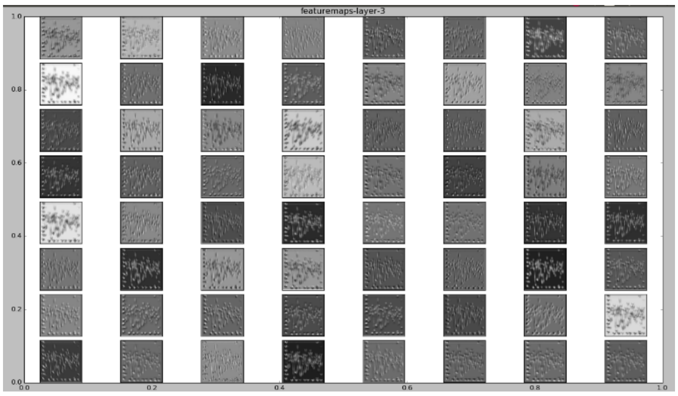


Fig. 9. The images obtained by passing network layers

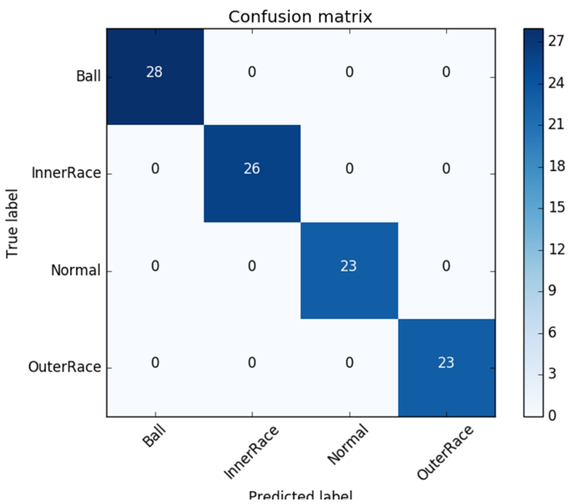


Fig. 10. Confusion matrix of the proposed method

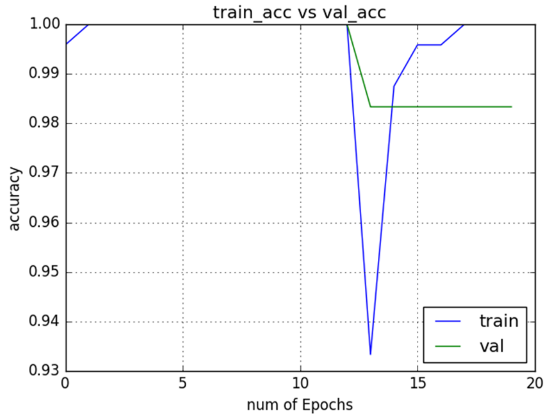


Fig. 11. Comparison of training accuracy with validation accuracy by epoch

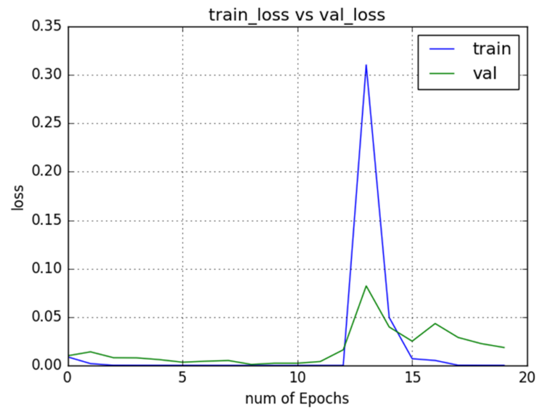


Fig. 12. Comparison of training loss with validation loss by epoch

TABLE I. CLASSIFICATION PERFORMANCE METRICS

Class	Recall	Precision	F1-Measure	Support
Normal	1.00	1.00	1.00	23
Ball	1.00	1.00	1.00	28
Inner race	1.00	1.00	1.00	26
Outer race	1.00	1.00	1.00	23
All categories	1.00	1.00	1.00	100

IV. CONCLUSIONS

The rolling element generate a vibration signal. The malfunction of the rolling machines affects the working performance of the machine. By inspecting these signals, it is possible to determine whether there is a fault in the machine. Signal processing, expert knowledge and human effort are required in traditional diagnostic approaches in order to diagnose vibration faulty signal. There are many studies in the literature to diagnose defective signals. Deep learning technology has been applied in many areas, mainly image classification studies. In this study, fault diagnosis has been provided by using Deep learning architecture without needing expert knowledge and human effort. Four categories of vibration signals are classified in this study. A deep learning model is proposed using CNN architecture to classify these four categories of signals. Network training has been completed by using 400 vibration signal data for training phase. 400 training data, 100 test data and 60 validation data have been used in the proposed method by the 20 epoch. Accuracy, recall, specificity and precision values of the proposed method have been obtained as 100%. The proposed study has been conducted in the Python programming language using the Keras deep learning library.

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