

A Review on Convolutional Neural Network in Bearing Fault Diagnosis

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Abstract. As the degradation of bearing yield to an enormous adverse impact on machinery and the damage that comes within could jeopardize human precious life. Hence, the bearing fault diagnosis is indisputably indispensable. This paper is predominantly focused on the utilization of Convolutional Neural Network (CNN) in bearing fault diagnosis of the rolling bearing. By deployment of CNN, an accurate diagnosis can be achieved without the necessity of pre-training the data. The function of CNN in diagnosing the bearing and architecture development of CNN are discussed. Lastly, to establish new and significant contribution in this area, new challenges are pinpointed.

1 Introduction

Bearing is a device used to enable rotational or linear movement while diminishing friction and coping the stress [1]. The most common used bearing in the rotating machinery is rolling-element bearing which comprises of rolling bearing and ball bearing. Rolling-element bearing also known as a rolling bearing is a complex system with inner rings, outer rings and rolling element. The difference in both bearing is at the rolling element shape, which are cylindrical and spherical shape respectively. The review is predominantly focused on the rolling element bearing as it is the most significant component in rotating machinery for its performance would directly influence the machine [2–4].

For decades, bearing has represented as main source of faults in equipment. In Georgoulas [5] and Bianchini [6] research, it is pinpointed that bearing can constitute 44% and 40% respectively of the total number of faults in some devices. As bearing degradation could yield vast impact on the performance, stability and life span of the rotating machinery [7], thus bearing fault diagnosis is indubitably very crucial. On top of that, bearing failure could engender to a catastrophic event such as

unforeseen delay, exorbitant cost and even human casualties [1,7]. Therefore, the past decades have perceived an increasingly number of comprehensive researches in bearing fault diagnosis [8]. Up till now, the drive of the researchers has never ceased in bearing fault diagnosis as it remains as an exigent complication which demands for a better and uncomplicated diagnosis *modus operandi* [9–12].

Not until three years ago, deep learning approach has sustained many attentions in machinery fault diagnosis [1–4]. Previously, deep learning approach is only utilized in the classification part of fault diagnosis whereby the features are extracted by various signal analysis methods and then used to train and test the DNN models [3–16]. In the recent years, DNN has been employed in both feature extraction from vibration data and classification of fault diagnosis [17–23]. Sundry, deep learning models has been successfully employed in fault diagnosis such as deep belief network [24,25], deep auto encoder [26–28] and convolutional neural network [29–32].

In this paper, the utilization of convolutional neural network (CNN) in diagnosing bearing fault diagnosis is reviewed. CNN is widely employed for analysis and classification process attributable to its significant ability in image processing and pattern

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recognition. For instance, CNN in image processing and pattern recognition is already practiced in medical field [62–64], face recognition [65–67], text identification [68–70] and language processing [71,72]. Formerly, in fault diagnosis, CNN is only applied to automatically select features from the generated vibration signal which is in one-dimensional input. Although the direct usage of CNN on the generated vibration signals is widely used and step-less, only time data could be extracted whereas the significant spatial data of the signals could not be interpreted. Therefore, the image input in using CNN is immensely essential. Within the next few years, image processing in bearing fault diagnosis will surely blossoming rapidly in mechanical industry.

Figure 1 illustrated the type of bearing fault diagnosed in most literature which are outer ring fault, inner ring fault and ball fault [33–37]. Kateris [38] claimed that of all faults in rolling bearings, the most recurrent faults occurred is cracks on inner and outer races with 90% while cracks in balls or cages represent 10%.

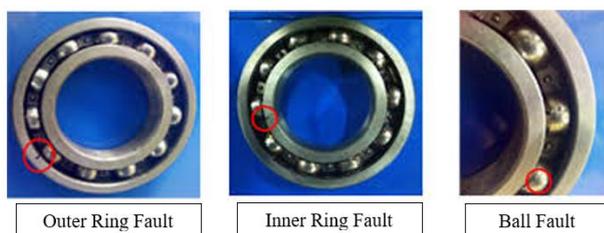


Fig.1. Faults Type in Physical Bearing

2 Convolutional Neural Network

CNN is the successful deep learning algorithm based on Artificial Neural Network (ANN) and biologically inspired by mammalian visual cortex[39–41]. Based on three ideas which are local receptive fields, shared weight and spatial subsampling, CNN incorporate limitation and achieve some degree of shift invariance [42]. The layers within the CNN are comprised of neurons that are organised into three dimensions, the spatial dimensionality of the input (height, width and depth). Generally, CNN consists of three type of layers which are convolutional, pooling and fully-connected layer [43]. As stated in [44], CNN is built up from multi stage neural network which consists of some filter stages and one classification stage. The convolution and pooling layer are part of filter stages along with another two types of layer which are batch normalization and activation layer. Several fully connected layers made up the classification stage

which is a multilayer perceptron. The basic architecture of CNN is shown in Figure 2 below.

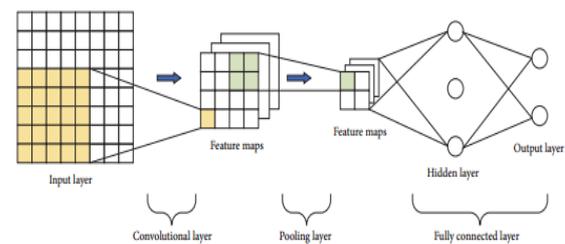


Fig.2 Basic Architecture of CNN

2.1 CNN Architecture

Throughout the years, the modification of CNN architecture has been made to improve its performance in diagnosis process. The very first modern framework of CNN was published by Le Cun [45] which called LeNet. There were many basic architectures of CNN proposed since then. A study made by Lee[46] has shown the effectiveness of CNN with sparse architecture of 1-layer and low amount of filter to classify bearing fault data of single-channel and dual-channel raw vibration signal data sets. He suggested that a 1-layer architecture of CNN with low amount of filter is more stable than 3 layers of CNN.

A CNN architecture composed of two filter stages and one classification stage is proposed by Wei[47]. He found that the proposed architecture can diagnose more accurately when compared with standard Artificial Neural Network (ANN). However, author did not perform a comparison between the proposed CNN architecture with the basic CNN architecture thus, the improvement cannot be fully manifested.

In 2016, Jinjiang et al [48] has proposed an enhanced CNN by introducing combination of two methods which are deep restricted neuron and dropout technology. He replaced sigmoid activation function with ReLU activation function in the conventional CNN and inserted a dropout technique in the fully-connected layer. The proposed method has managed to solve the low convergence rate in conventional CNN and yield escalation of 8% accuracy.

Verstraete [29] has modified the CNN architecture by inserting two stacked of convolutional layer before a pooling layer. He claimed that the stacking of

convolutional layer brought advantage to reduce the parameters numbers that must be learnt and increasing the expressivity of the feature. The proposed architecture showed that it is robust against experimental noise with low computational cost as the number of learnable parameters has been reduced.

The finding in [46] is in contrast with finding in Guo [18] study as the increment of total number of ConvNet layer that consist of a convolutional layer and a pooling layer from one to three layers has manifested a rise of 8% in diagnosis accuracy when juxtaposed with traditional deep convolutional neural network. Author also proposed a novel hierarchical structure model of deep convolution neural network comprising of fault pattern determination layer and a fault size evaluation layer.

Up until now, there is only one proposed bearing fault diagnosis model that include fault diagnosis and fault severity hierarchically. To the best of author knowledge, most reported work does not include the severity of the bearing degradation in the diagnosis. The evaluation of bearing fault severity is prior to determine the urgency of bearing replacement. Yang [103] claimed that the defect size of bearing of 0.007 inch is considered small thus there is no urgency in maintenance as the significance residual life of the bearings will be lost. Cerrada [73] addressed the fault severity into low, medium and high level. Most of the reported work used data extracted from Bearing Data Center of Case Western Reserve University (CWRU) cite whereby 0.007, 0.014 and 0.021 inches of depth of fault in bearing are used. Al-Bugharbee [104], Li [105], Zhou [21] and Haddad [106] indicated the respective fault depths into slight, medium and severe.

If the bearing with slight defect is replaced early, the significance residual life of the bearings will be lost. Therefore, the severity of the faulty bearing degradation is very important in fault diagnosis of bearing thus, having both process in a system would make the bearing fault diagnosis model become a reliable and exemplary.

2.2 CNN in Bearing Fault Diagnosis

Previously, CNN is only implemented to classify the bearing fault condition. The feature extraction and learning part is done using other approaches. In Bhadane [49] study, he employed CNN only for classification purpose by fed the CNN with the statistical features extracted from the vibration data. He found that CNN performed well in classifying faults compared to traditional intelligent diagnosis

method such as SVM and KNN. While Xie [30] found combined method could yield a greater output in classification compared to CNN only. He utilized CNN for classifying bearing fault while extracting features part is executed using discrete wavelet transform (DWT).

Most of the researchers are still employing traditional diagnosis method in feature learning. Table 1 summarizes the usage of method for feature extraction which then fed into CNN for classification. Regardless of the noteworthy performance of the feature extraction process by other method, the use of deep learning approach in feature extraction process should be investigated more rapidly to lessen the dependability on the expertise and experience of the experts.

Table 1 Comparison of Method for Feature Extraction Process

Method +CNN	Model Accuracy [%]	References
Haar Wavelet	99.44	[30]
db2 Wavelet	99.6	[30]
sym3c Wavelet	99.78	[30]
bior3.1 Wavelet	98.57	[30]
dmey Wavelet	99.74	[30]

In the recent study, the researchers are motivated to deploy CNN to not only function in classifying faults but also in feature extraction and learning. They are driven to investigate the capabilities of CNN in diagnosing the fault without any preprocessing of the raw signal. Studies in recognition and detection tasks in image and speech analysis has shown that CNN has become the supreme approach and successfully applied to learn features from raw data [50,51]. Thus, more works is dedicated in applying CNN directly on raw vibration data for fault diagnosis. Additionally, through multiple non-linear transformations and general complex non-linear functions, deep neural networks approach i.e. CNN can encapsulate the information carried from raw signals with minimal error [18].

Ince [39] claimed that he was among the pioneer that employ 1D CNN that functioned as feature extractor and classifier to detect fault in mechanical system. As the proposed method could learn directly from raw data and any transformation or post processing are not required, low computational cost could be achieved. Therefore, enabling the real-time fault detection. He also managed to achieve more than 97% accuracy of classification process with less dependence to experts and signal preprocessing time.

Then, Jing et al. [52] has added SoftMax regression layer as the last layer to increase accuracy and fast computation. CNN was used to learn feature directly from raw data and produce the diagnosed result. He uncovered that CNN outperforms the traditional machine learning such as support vector machine (SVM) in feature extraction and classification as the accuracy escalates in amount of 10 percent. Author also scrutinized the effectiveness of CNN in learning from different data types and made a hypothesis that CNN would work better with 2D than 1D data.

The hypothesis by Jing et al. [52] is then validated by Zhang [47] study where he noticed the 2% increase in diagnosing accuracy when signal image is being fed into CNN compared to when using raw data as input. A study of employing CNN with image representation of vibration signal as the input also presented by [29]. In his study, he probed the most effective form of image representation of vibration signal and found that scalogram is the best in representing signal compared to Hilbert images and spectrogram. The comparison of the time-frequency method in visualizing the signal into 2D form is summarized in Table 2 below.

Table 2 Comparison of Time-Frequency Method for Visual Representation of the Raw Signal

Time-Frequency Method + CNN	Model Accuracy [%]	References
Short Transfer Fourier Transform (Spectrogram)	99.5	[29]
Morlet Wavelet Transform (Scalogram)	99.5	[29]
Hilbert Huang Transform	97.6	[29]

Image Transformation	99.9	[47]
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Despite the researches that work on feeding the CNN with the 2D visualization of the raw signal, the best time-frequency method in representing the raw signal is still uncertain. There are still inadequate researches that works on the capability of CNN in image processing in mechanical fault diagnosis. Not until in the very recent that researcher realize the potential of CNN in pattern recognition based on image analysis in mechanical diagnosis.

Regardless of the magnificent performance of CNN in bearing fault diagnosis, until now, the practice of CNN in real-time bearing fault diagnosis is a failure. The industries are still in the start-up phase, CNN based bearing fault diagnosis is difficult to practice in industries because the enormous amount of labeled data is hard to acquire. The major drawback of CNN is the need for huge amount of data as the small sample of data may lead to overfitting[53]. Even though, the huge amount of bearing labeled data is accessible form the internet but, in real-time practice, it is not easy to acquire bearing labeled data especially for a new machinery. It is going to take a lot of experiments to obtain huge amount of data thus other method approach in overcoming the drawback of CNN must be considered.

3 Conclusion

In this paper, the utilization of CNN in bearing fault diagnosis has been reviewed. Few works have proposed the architecture of CNN that diagnose the bearing faults with its severity. The bearing fault diagnosis model should include the severity of the bearing degradation as it is vital in determining the urgency of faulty bearing replacement. The best input of 2D images that visualizes the raw signal which will be fed into CNN should be investigated. Finally, the method to vanquish the limitation of CNN to diagnose the bearing faults in real-time application should be explored.

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