Review on Vibration Signal Analysis of Rotating Machinery Based on Deep Learning

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Abstract. Rotating machinery is widely used in industrial systems, and its operation state is directly related to the working performance of the system. Research on equipment condition monitoring and fault diagnosis based on vibration signal analysis is of great significance to ensure the safe and stable operation of equipment. In recent years, the field of deep learning has developed rapidly, and many researchers have applied it to the vibration signal analysis of rotating machinery equipment. Firstly, the development history of deep learning is reviewed. Then, the principles of deep learning models such as convolutional neural network, deep belief network, stacked auto-encoder and their applications in vibration signal analysis of rotating machinery are introduced. Finally, the future development trend of deep learning is discussed.

1. Introduction
Rotating machinery refers to machinery that mainly relies on rotation to complete specific functions. They are widely used in power, petrochemical, port handling, automobile manufacturing, aerospace and other industries. Once the equipment fails, it will affect the normal operation of the equipment. Seriously, it will lead to equipment shutdown and even significant property losses and casualties. Therefore, on-line monitoring and fault diagnosis of rotating machinery has become a key part of system design and maintenance. Oil analysis, temperature analysis, acoustic emission detection, vibration analysis and other diagnostic and test methods are the main means of fault feature extraction and fault diagnosis\textsuperscript{[1]}. Compared with other monitoring methods, the conditions required for vibration signal analysis are easier to obtain. Therefore, the method based on vibration signal analysis has been effectively applied in the field of rotating machinery. The traditional vibration signal analysis method firstly uses wavelet transform\textsuperscript{[2]}, empirical mode decomposition\textsuperscript{[3]}, ensemble empirical mode decomposition\textsuperscript{[4]}, empirical wavelet transform\textsuperscript{[5]}, variational mode decomposition\textsuperscript{[6]} to analyze and extract the fault characteristics of the vibration signal, and then classifies the fault by pattern recognition method. Such methods not only need more prior knowledge, but also have limitations in dealing with big data. The proposal of deep learning\textsuperscript{[7]} provides a solution to this problem. Deep learning aims to simulate the human brain and establish a neural connection structure model. When processing different signals, the extracted data features are transformed and stratified, and then described. Because the deep learning model has strong self-learning ability, and can discover the connection between data when processing massive data, and automatically extract useful information,
which highlights the ability of deep learning in dealing with complex recognition problems. It has attracted many scholars to study the theory of deep learning.

In recent years, deep learning has provided new ideas and methods for vibration signal processing of rotating machinery with incomparable advantages over other methods. This paper analyzes three main models of deep learning and summarizes the outstanding achievements made by predecessors in the field of vibration signal analysis based on deep learning from January 2017 to December 2020, and points out the challenges of deep learning in vibration signal processing of rotating machinery.

The rest of this paper is organized as follows: Section 1 details the theoretical framework of three mainstream deep learning methods; The second section summarizes the achievements of deep learning in the field of vibration signal analysis of rotating machinery. The third section summarizes the full text and discusses the future development trend of deep learning.

2. Overview of Deep Learning
In this section, we briefly introduce the theoretical knowledge of three basic frameworks of deep learning, including convolutional neural network (CNN), deep belief network (DBN) and stacked auto-encoder (SAE).

2.1. Convolutional neural network
Convolutional neural network (CNN) is a feedforward neural network proposed by LeCu inspired by the sensory mechanism of animal visual cortical cells [8], which is one of the most representative algorithms in the field of deep learning and has been widely applied to the field of image processing [9–10]. Convolutional neural network is generally composed of convolution layer, pooling layer and fully connected layer. Fig 1 shows the structure diagram of CNN processing vibration signals. The convolution layer is also called the feature extraction layer. The convolution layer convolutes the previous layer through different convolution kernels, and each convolution kernel corresponds to an extracted feature, which has the advantage of self-extracting features. The pooling layer, also known as the down-sampling layer, is generally located in the middle of the continuous convolution layer, which can sample the data of each dimension and further reduce the data scale. It can reduce network parameters and computation, and control overfitting. The vibration signal processing based on CNN has the following advantages:

(1) compared with the traditional neural network, CNN has stronger learning ability, which can self-learn the characteristics of massive data and is suitable for processing high-dimensional data;
(2) CNN is suitable for multi-source information processing, not limited to data, its input can be spectrum, time series, etc;
(3) it can effectively deal with the complex problems of environmental information, and has good self-learning, self-processing, and high fault tolerance.

Fig 1 CNN structure diagram
2.2. Deep belief network

Deep Belief Network (DBN) is a neural network algorithm proposed in 2006\cite{11}, whose core is to train and optimize the connection weights of neural networks by unsupervised learning, as shown in Fig 2. A typical DBN framework consists of several restricted boltzmann machine (RBM) and a single-layer BP neural network. The lower level DBN can extract lower level features, while the higher level is used to represent more abstract features of input data. DBN is applied in both supervised learning and unsupervised learning. When used as unsupervised learning, it can reduce the dimension of vibration signals and extract features. When used as supervised learning, it can be used as a classifier. In recent years, DBN has been widely used in the field of prediction\cite{12,13}. DBN is one of the earliest non-convolution models to realize deep structure training, and its proposal has promoted the development of deep learning. Vibration signal processing based on DBN has the following advantages:

1. without relying on signal processing technology, it can adaptively extract features and realize intelligent processing;
2. it can deal with high-dimensional, nonlinear, non-stationary vibration signals and is suitable for processing large amounts of data;
3. DBN represents the data into a probability model through unsupervised learning, which is suitable for the sample generation expansion of small samples in industrial processes.

![Fig 2 DBN structure diagram](image)

2.3. Stacked auto-encoder

Auto-encoder (AE) is a typical unsupervised neural network model, whose core function is to extract the deep expression of input data\cite{14}. SAE is an important application form of AE, which is stacked by multiple AEs. With the concept of deep learning proposed in 2006, SAE is gradually used to learn to generate model data\cite{15}. Fig.3 shows a typical SAE model composed of a basic AEs. In the implementation process of SAE, multiple AEs are superimposed serially, and the feature expression (H) of the previous AE is used as the input of the next AE, while the output part of the previous AE is discarded. SAE can obtain more abstract and essential feature expression of input data through multiple AE feature extraction, and its output can be regarded as the deep feature expression of input data after feature extraction\cite{16}. SAE-based vibration signal processing has the following advantages:

1. vibration signal is mostly one-dimensional signal, SAE has a simple structure and is suitable for processing vibration signal;
2. SAE can effectively reduce the influence of signal noise adaptively without signal preprocessing;
3. SAE can use a small amount of data samples for training, and has strong feature extraction ability and robustness. Combined with other classification technologies, SAE can achieve efficient fault diagnosis.
3. Application of deep learning in vibration signal analysis

With the development of deep learning, convolution neural network, deep belief network, stacked auto-encoder and other methods have been widely used in the field of vibration signal analysis of rotating machinery, and have achieved rich results. He Zongbo\[17\] applied one-dimensional convolution neural network(1D-CNN) to the vibration signal processing of bearings, and directly input the original signal data into the model to complete the fault diagnosis. Niu Naiping\[18\] constructed 1D-CNN fault diagnosis model acting on the time-domain vibration signal, and applied it to the fault diagnosis of shearer rocker arm gear, and achieved good results. Lu yangJing\[19\] directly input the original data of gearbox vibration signal into the CNN, and directly obtained the diagnosis results. Zhou Qicai\[20\] proposed a vibration signal analysis method of rotating machinery based on 1D-CNN, and the results show that the method has high robustness. Liu \[21\] proposed a multi-task one-dimensional convolutional neural network (MT-1DCNN) for bearing vibration signal analysis, and obtained accurate diagnosis results. Wen L\[22\] proposed a new ensemble CNN with diversity regularization for bearing vibration signal analysis, and the results show that the proposed method has potential performance in the field of vibration signal analysis. Wu C \[23\] focuses on developing CNN to learn features directly from the original vibration signals and then diagnose faults. Zhang W\[24\] proposed a new training interference CNN method, which directly uses the original vibration signal to realize the fault diagnosis of rolling bearings under noise environment and different workloads. The results show that the training interference CNN has better diagnostic performance than the traditional CNN. Xu Z\[25\] developed a novel improved multi-scale coarse-grained process convolution neural network with feature attention mechanism, which can directly process the original vibration signal, so as to achieve accurate fault diagnosis of rolling bearings in complex actual situations. Shao \[26\] proposed a deep learning model based on DBN, which uses the effective modeling ability of DBN to model high-dimensional data and learn multi-layer features, so as to reduce the training error and improve the classification accuracy. Che\[27\] proposed an adaptive deep belief network (DA-DBN) for the vibration signal analysis of rolling bearings. Li Yiping\[28\] proposed a deep belief network based on PSO optimization to solve the problem of long time adjustment of DBN, and used the optimized DBN model to extract low-dimensional fault features from the original vibration signal. In order to reduce the dependence on manual experience, Fan \[29\] used DBN model to extract health indicators directly from the original vibration signals of bearings. Yan \[30\] proposed a rotor imbalance fault diagnosis method using DBN to automatically learn representative features and accurately identify fault states. Lu\[31\] used the stacked denoising auto-encoder to process the vibration signal of the rotating mechanical system, which proved that this method had better durability under various working conditions and environmental noise. As an unsupervised deep learning algorithm, SAE can reduce the pressure of tag data. Due to the diversity and variability of the actual fault diagnosis distribution, Sun \[32\] proposed an optimized transfer learning algorithm to solve the adaptive problem. Alabsi\[33\] used SAE to extract features of bearing vibration signals, and compared with traditional methods to prove its superiority. SHAO\[34\] proposed a fault diagnosis method for rotating machinery based on SAE.
feature learning to solve the problem that it is difficult to automatically obtain effective fault features from the vibration signals measured by rotating machinery.

4. Summary
With the continuous development of deep learning, more and more scholars apply deep learning theory to various industries, bringing new ideas to many industries. This paper briefly reviews the principles of convolution neural network, deep belief neural network and stack autoencoder which are widely used in the field of vibration signal analysis of rotating machinery and equipment, and sorts out the relevant literature from 2017 to 2020. The author believes that there are still several aspects to be further studied:

(1) The existing deep learning models are various. According to the characteristics of a specific equipment vibration signal, designing a suitable deep learning model may be the trend of future development;
(2) Traditional vibration signal analysis methods mainly include signal preprocessing, feature extraction, pattern recognition and other stages. Deep learning is a way to divide vibration signals from 'port' to 'port'. Whether it can be combined with traditional methods is worth studying;
(3) In the actual industrial system, the fault features contained in the vibration signal may be less or unbalanced. How to effectively solve this problem by using deep learning theory may be an important direction for future research.

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