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Research on Computer Big Data Deep Learning Technology in Mechanical Processing

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Abstract—**Aiming at the problems that traditional manufacturing and processing equipment is not closely related to data and information in the production and processing process, and the use and maintenance of equipment relies on manual experience, a new method of equipment intelligence is proposed. There are faults in motor manufacturing during machining. Based on the non-stationary and non-linear nature of the motor signal itself, combined with the characteristics of large amount of motor monitoring data and the advantages of deep learning methods in target recognition, this paper proposes a fault diagnosis method for motor machining based on deep learning.**

Keywords—motor failure, machining, deep learning, motor signal, fault system

I. Introduction

Key technologies such as artificial intelligence and advanced control continue to develop, and intelligent manufacturing is bound to be the vane of future manufacturing development. Digital twin technology is a technology that describes object models in the physical world in the information world in a digital way of expression. The integration of physical information and virtual information is the key to driving the comprehensive digitalization of modern industrial society. Digital twin technology is one of the physical worlds and the information world. A higher level of productivity. Deep learning technology uses artificial neural networks such as deep learning networks, convolutional neural networks, and recurrent neural networks to automatically extract high-dimensional features from big data and output prediction information [1]. The problem to be dealt with is an important technology that ultimately realizes the worlds of manufacturing and processing equipment and enables manufacturing and processing equipment to have self-perception and self-decision-making capabilities. By establishing a digital twin of manufacturing and processing equipment, the production cycle can be greatly shortened. It can greatly improve the intelligence of manufacturing and processing equipment.

Motors are used more and more widely in contemporary social production systems. They are the main driving equipment for industrial production activities. Once they fail, they will bring huge economic losses [2]. Therefore, the research on fault diagnosis technology of motor manufacturing has important theoretical research value and practical significance. In view of the above analysis, in order to realize the fault diagnosis of motor manufacturing, this paper proposes a deep learning-based method based on the non-stationary and non-linear nature of the motor signal itself, combined with the large amount of motor monitoring data and the advantages of deep learning methods in target recognition. Fault diagnosis method for motor manufacturing.

II. Stacked noise reduction deep learning self-encoding theory

A. Auto encoder

Autoencoder (AE) is a three-layer unsupervised network, as shown in Figure 1. The first two layers are the encoding part, and the latter two layers are the decoding part. The idea is to use the back propagation algorithm to make the output value of the network equal to the input value, that is $y^{(i)} = x^{(i)}$.

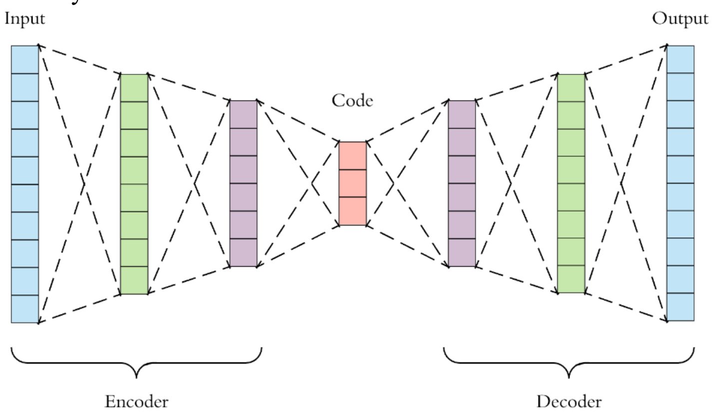

Fig. 1. Autoencoder

Encoding is to map the input sample $x^{(i)}$ to a low-dimensional space through an activation function, as shown in equation (1).

$$h_{w,b}(x) = f_{(\theta)}(x^{(i)}) = f(w \cdot x + b) \tag{1}$$

Where: $x^{(i)}$ is the sample, i is the number of samples, $f(\cdot)$ is the activation function, $\theta = \{w,b\}$ is the network parameter, w is the weight, and b is the bias. Decoding is to reconstruct the sample $x^{(i)}$ by mapping the $h_{(w,b)}(x)$ in the low-dimensional space to the high-dimensional space through the activation function, as shown in equation (2).

$$\hat{x} = f_{(\theta')}(h_{(w,b)}(x)) = f(w' \cdot h_{(w,b)}(x) + b') \tag{2}$$

The method of training self-encoding is to back-propagate the error to adjust the weight W and bias B of each layer, so that the error converges and reaches a minimum.

$$J(x,\hat{x}) = \frac{1}{m}\left\|\hat{x} - x\right\|^2 \tag{3}$$

In the formula, J is the objective function and m is the number of samples. If the error $J(x,\hat{x})$ reaches the minimum, that is, when $x^{(i)}$ and $\hat{x}^{(i)}$ are infinitely close, then it can be said that $h_{(w,b)}(x)$ is a good representation of the sample, that is, a good feature expression of the sample.

B. Noise reduction self-encoding

In practical applications, some part of the data loses its authenticity due to the influx of noise in the training sample data (for example, the vibration signal of a motor is disturbed by noise at a certain moment, and the characteristics of the signal cannot express the state of the motor). The features obtained by the AE method have errors due to the presence of noise. Denoising Autoencoder (DAE) adds noise to the training data on the basis of the autoencoder [3]. The encoder needs to learn to remove noise to obtain an input signal that is not polluted by noise, making it more robust. First, add random noise to sample x^n according to the distribution of q_D , as shown in equation (4).

$$\widetilde{x} \sim q_D(\widetilde{x} \mid x) \tag{4}$$

The optimization algorithm is used for multiple iterations to complete the training of the network. DAE adds random noise to the training samples, which reduces the impact of different distributions of training samples and test samples, and improves the robustness of feature expression.

C. Stacked noise reduction self-encoding

Stacked noise reduction auto-encoding (SDAE) is formed by stacking multiple DAEs to form a multi-level network structure [4]. Aiming at the fault diagnosis of motor manufacturing, this paper adopts a two-layer network structure composed of two noise-reducing autoencoders and a classifier, as shown in Figure 2. DAE1 is the first layer of noise reduction and self-encoding, DAE2 is the second layer of noise reduction and self-encoding, and SoftMax is the classifier.

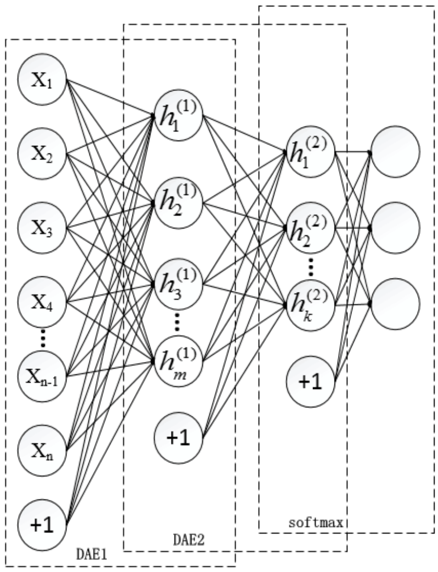

Fig. 2. SDAE network structure

III. Intelligent manufacturing and processing system platform

In order to establish a high-fidelity manufacturing and processing equipment digital twin in the information layer, and the digital twin can reflect the real state of the physical layer manufacturing and processing equipment in real time, the perfect integration of the physical layer data and the virtual model of the information layer is the key. Digital twin technology promotes the integration of physical layer data and information layer data, is an effective method to solve the above problems, and can provide new tools for the upgrading and transformation of the manufacturing industry. Based on the digital twin technology, an overall framework of intelligent manufacturing and processing equipment has been established, as shown in Figure 3 (picture quoted in A Cyber-physical System Architecture in Shop Floor for Intelligent Manufacturing).

The physical layer mainly includes two parts: the physical entity of the manufacturing and processing equipment and the physical sensor. The physical sensor is a sensor installed on each part of the manufacturing and processing equipment to collect various status and motion signals of the equipment during the processing [5].

The manufacturing and processing equipment in the physical layer is mapped to the information layer through the data mapping dictionary to generate the corresponding three-dimensional digital model. The three-dimensional digital model and multi-domain processing data are fused into a digital twin of the manufacturing and processing equipment, which exists in the manufacturing process. The entire life product cycle of the equipment can dynamically, truly, and real-timely reflect the true state of the manufacturing and processing equipment in the physical layer. In addition, real-time simulation, simulation, verification and decision-making can be carried out through the cloud decision-making platform.

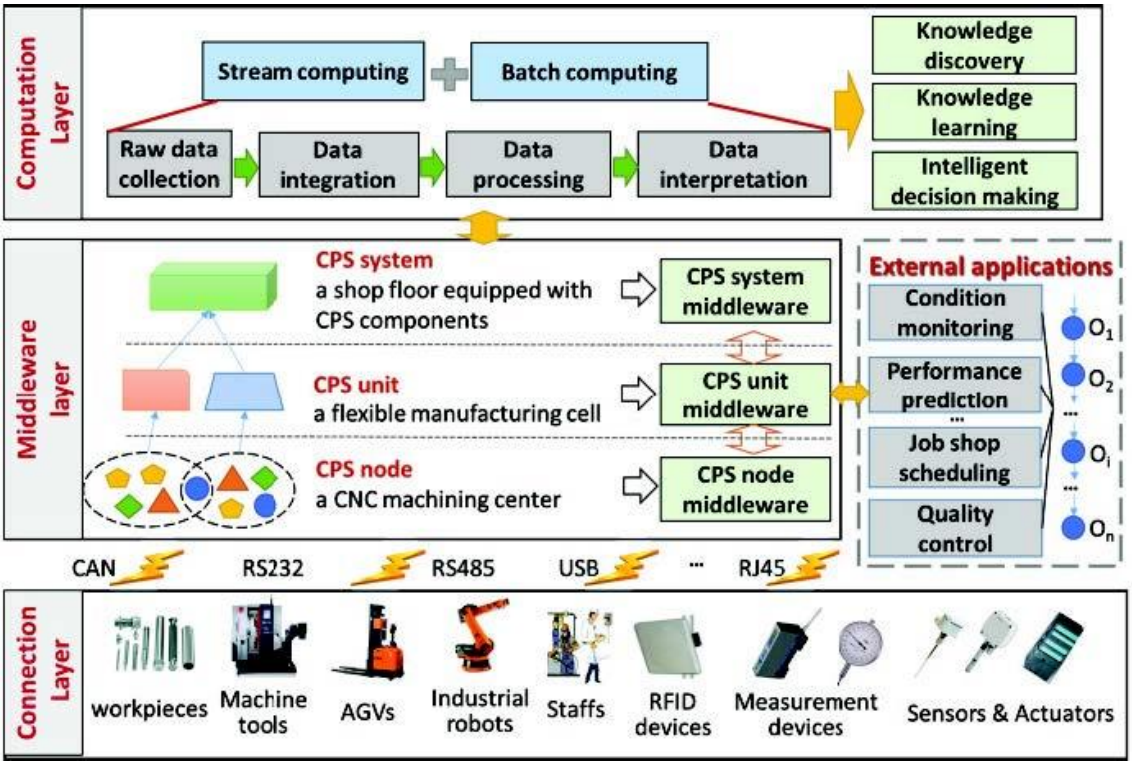

Fig. 3. The overall framework of intelligent manufacturing and processing equipment

The cloud decision-making platform is an important support for the digital twin to realize self-perception, self-prediction, and self-decision. Its core is deep learning technology.

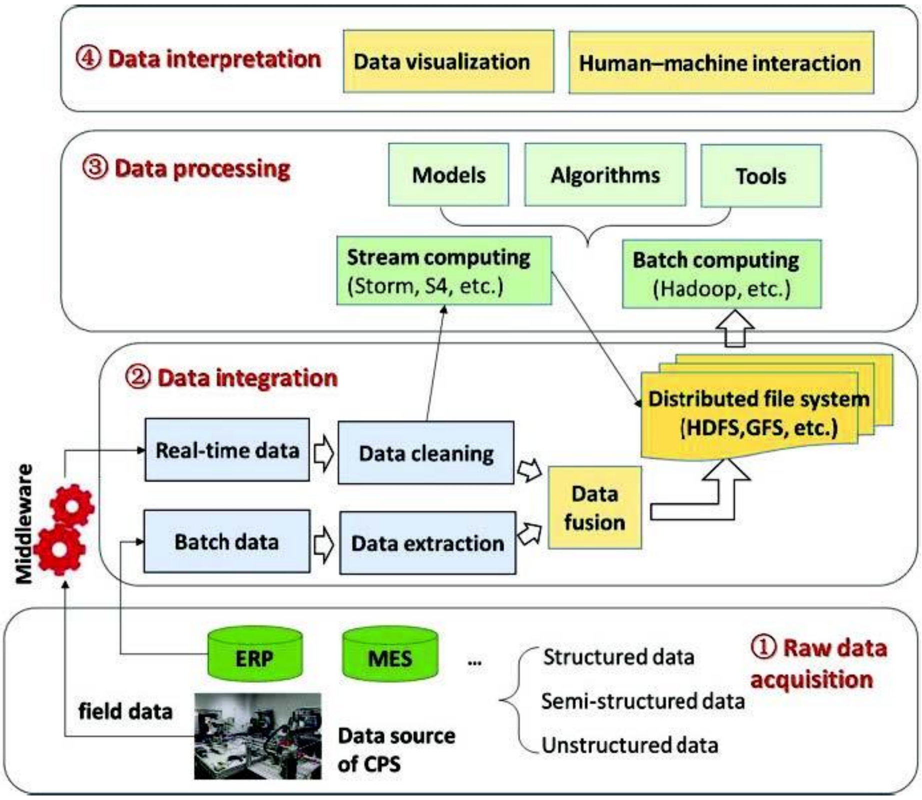

Fig. 4. Decision-making and optimization process of manufacturing and processing equipment based on deep learning

IV. SYSTEM IMPLEMENTATION

The application of deep learning technology reduces the burden of manually extracting features from machine learning models, especially in the image and voice capture and classification. Among them, convolutional neural networks and recurrent neural networks are commonly used deep learning technologies. Through the artificial neural network, real-time prediction and perception of fault diagnosis, maintenance detection, equipment status monitoring, error analysis, etc. during the operation of manufacturing and processing equipment can be realized, so as to realize the transformation of manufacturing and processing equipment from passive management and control to active predictive management and control [6]. The historical big data generated in the processing process is used to drive the training process of the artificial neural network (Figure 4). Through the digital twins and sensors of the manufacturing and processing equipment, the processing data is monitored in real time to realize the condition monitoring of the equipment and the prediction of unknown factors. Correction, on the other hand, can update and expand historical data based on real-time monitored data.

V. Fault diagnosis of motor manufacturing based on deep learning method

This paper takes the asynchronous motor of the multi-stage gear transmission system as the research object, and monitors and diagnoses its health status through the SDAE network and STFT+CNN methods. Use SDAE to analyze and diagnose the three types of samples in the time domain, frequency domain, time domain and frequency domain of the motor respectively. First, build the N layer SADE ($N = 2,3,4,5,6$), and use the time-domain signal of the motor fault as the input of the network. After multiple iterations, the result is shown in Figure 5 (the picture is quoted from Understanding Human-Centric Images: From Geometry to Fashion). Secondly, the N layer SADE ($N = 2,3,4,5,6$) is constructed, and the frequency domain signal of the motor fault is used as the input of the network. Finally, the N layer SDAE ($N = 2,3,4,5,6$) is constructed, and the combination of the time domain and frequency domain signals of the motor fault is used as the input of the network, after many iterations.

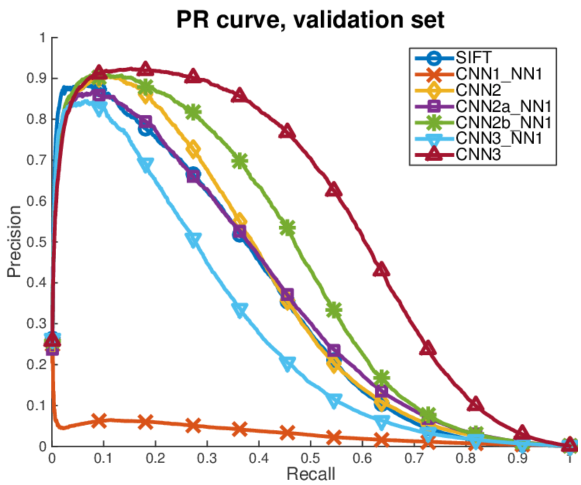

Fig. 5. Renderings of networks with different depths

It can be seen from Figure 5 that with time domain samples as input, when a 5-layer network is established (the network model is:), the error rate of the motor manufacturing fault diagnosis results is the lowest, that is, the correct rate is 97.57%, as shown by the red triangle Show. Therefore, it can be seen that when the time domain signal is used as an input sample, it is not that the deeper the network layer, the better the diagnosis effect. When two types of samples in frequency domain, time domain and frequency domain are used as network input, the error rate of fault diagnosis is 0, that is, the correct rate is 100%, as shown by the green circle and black asterisk line. However, the deeper the number of network layers, the greater the amount of calculation, so it is sufficient to choose a two-layer SDAE network (frequency domain: time domain combined with frequency domain:) for fault diagnosis in motor manufacturing. In order to compare with traditional intelligent methods, this paper also uses wavelet decomposition + BP neural network, EMD + SVM, PCA + SVM, diagnostic feature + SVM four methods to diagnose motor faults, the results are shown in Table I.

TABLE I. Results of different fault diagnosis methods for motor manufacturing

Method	Sample	Number of samples	Diagnostic accuracy
Wavelet + BP	Time domain signal	9100	14.29%
PCA+SVM			30.52%
EMD+SVM			93.67%
Diagnostic features + SVM			95.05%
CNN	Time-spectrogram	14000	100%
SDAE	Time domain + frequency domain signal	9100	100%

Since wavelet needs to manually select wavelet basis functions when decomposing signals, different wavelet basis functions have a greater impact on the decomposition, and EMD can decompose signals adaptively; in addition, BP neural networks have the disadvantage of being easy to fall into local optimal solutions. Therefore, the effect of wavelet analysis + BP method is poor, and its diagnostic accuracy is only 14.29%. PCA is essentially a linear method, and its ability to deal with nonlinear problems is poor. Therefore, the PCA+SVM method has a poor effect and its diagnostic accuracy is 30.52%. The diagnostic accuracy of EMD+SVM and diagnostic feature + SVM are 93.67% and 95.05%, respectively, which shows good results in fault diagnosis of motor manufacturing. SDAE uses the deep network to adaptively extract features that can be more accurate, and supervise the fine-tuning of the entire network, so as to efficiently realize the intelligent diagnosis of motor faults, with a diagnosis accuracy of 100%. However, CNN can accurately realize fault diagnosis of motor manufacturing due to the multi-layer network mapping and supervised parameter adjustment, and its diagnosis accuracy is 100%.

VI. Conclusion

The diagnosis method based on short-time Fourier transform combined with convolutional neural network can accurately realize the fault diagnosis of motor manufacturing and make up for the shortcomings of traditional signal processing methods in the face of complex and nonlinear signals. Compared with traditional signal processing methods, there are insufficient features in the extraction of motor signal features-unable to accurately extract the feature expression representing the fault, the SDAE method can adaptively extract the features representing the signal fault, making the fault diagnosis more accurate.

References

[1] Liu Yan, Feng Zhijie. Application of SSD deep learning algorithm in manipulator grasping system. Modular Machine Tool and Automated Processing Technology, vol. 556, pp.72-75, June 2020.

[2] Liu Guoliang, Yu Jianbo. Machining roughness prediction based on knowledge depth belief network. Journal of Mechanical Engineering, vol. 55, pp.108-120,Twenty 2019.

[3] Ni Chao, Li Zhenye, Zhang Xiong, et al. Seed cotton film sorting algorithm based on shortwave near-infrared hyperspectroscopy and deep learning. Transactions of the Chinese Society of Agricultural Machinery, vol. 50, pp. 170-179,December 2019.

[4] Wang Anbang, Sun Wenbin, Duan Guolin. Research on Intelligent Method of Manufacturing and Processing Equipment Based on Digital Twin and Deep Learning Technology. Journal of Engineering Design, vol. 26, pp. 9-28,June 2019.

[5] Wu Chunzhi, Feng Fuzhou, Wu Shoujun, et al. Application research review of deep learning in fault diagnosis of rotating machinery equipment. Noise and Vibration Control, vol. 39, pp.7-11,May 2019.

[6] Zhang Lizhi, Tan Jiwen, Xu Weixiao, et al. Rolling bearing fault diagnosis based on decision fusion of multiple deep learning models. Modular machine tool and automated processing technology, vol.10, pp.59-62,August 2019.