Fault diagnosis method of mine hoist braking system based on deep convolution neural network

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Title page

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Abstract: A reliable braking system is an important guarantee for safe operation of mine hoist. In order to make full use of the monitoring data in the operation process of mine hoist, identify the operation status of the hoist, and further carry out fault diagnosis on it, the deep learning method was introduced into the fault diagnosis of the hoist, and a fault diagnosis method of hoist braking system based on convolution neural network has been proposed. Firstly, the working principle and fault mechanism of disc brake and its hydraulic station in hoist braking system are analyzed, and the monitoring parameters of this study are determined; then, based on massive monitoring data, the convolutional neural networks (CNN) is established, the one-dimensional signal collected by the sensor is transformed into two-dimensional image for coding, the neural network is trained by gradient descent method, and the network structure parameters are modified according to the training results. Finally, the fault diagnosis model is compared and verified by using the sample set based on the traditional back propagation neural network (BP) and CNN. The results show that the accuracy of CNN is higher than that of BP, and the accuracy rate can reach 99.375% after reducing the involvement between samples. This method can make full use of the monitoring data for diagnosis, without subjective intervention of experts, and improve the accuracy of diagnosis.

Keywords: deep learning; mine hoist; braking system; fault diagnosis; CNN

1. Introduction

Mine hoist is the key equipment that connects the underground and underground in the process of coal mining energy. Its safe and reliable operation is directly related to the economic benefits of coal mine enterprises and the life safety of coal production personnel. As an important part of the hoist, the performance of the braking system is directly related to the safety and reliability of the hoist. Therefore, relying on advanced sensor technology and dynamic testing technology to carry out accurate early forecast and diagnosis of the hidden fault is of great significance to ensure the safe operation of the hoist.

In recent years, many researchers (Mohammad and Hamzeh 2019; Khatib et al.2017; Mrugalski et al.2016; Li et al.2018; Si et al.2017) have applied new technologies such as artificial intelligence and neural networks to fault diagnosis. The system's technical architecture, development mode and key technologies have been discussed in depth, providing new ideas for the study of fault diagnosis methods. These methods have played a very good role in a single system, but most of these research methods are independent applications, resource utilization is not sufficient, and the performance of big data processing capabilities is mediocre.

With the continuous improvement of intelligent sensing and monitoring technology, as well as the increase of measuring points and the increase of sampling frequency, the monitoring data of equipment based on the operating conditions of the upgrade has the characteristics of large data volume, multiple data dimensions, and redundant data attributes. The existing diagnostic methods can no longer meet the rapidly growing data processing needs. Machine learning, as the most efficient data processing algorithm in the era of big data, has begun to emerge. This method studies fault characteristics on the basis of data. By collecting equipment operating data and analyzing and processing it, it extracts useful characteristic data for system failures. Diagnosis, especially in fault classification, has advantages that other algorithms cannot match. Li et al. (2020) proposed a C4.5 decision tree algorithm based on Kendall's harmony coefficient, and obtained a decision tree classification model, which improved the fault diagnosis accuracy when processing more data. Liu et al. (2012) used the method of decision tree construction to design the fault early warning system, which solved many problems such as passive detection of mine hoist fault detection, inaccurate fault data and detection delay. Li et al. (2014) carried out uncertainty inferences on mine hoist faults based on Bayesian theory, and got a better fault recognition effect. Vernekar et al. (2014) used support vector machines as a classifier to diagnose the faults of rolling bearings, which proved the superiority of machine learning technology in fault diagnosis. Yao et al. (2018) used an optimized support vector machine to diagnose the bearing fault of the train. This method can accurately identify the type of bearing fault of the train and improve the accuracy of classification.

The machine learning algorithm divides the problem into several parts, solves them separately, and then combines the results to obtain the required answer. Therefore, machine learning is particularly suitable for scenarios with small amounts of data. In contrast, deep learning solves problems in a centralized manner without having to split the problem. With the rapid increase in the amount of data, the effect of deep learning will become more prominent. Therefore, many scholars try to introduce deep learning technology into the research of fault diagnosis of mechanical equipment. Commonly used methods include deep belief networks, deep belief networks, CNN, auto-encoders, and recurrent neural networks.

Chen et al. (2019) analyzed the main literature on equipment health and failure prediction, discussed various architectures and related theories, and provided clear directions for subsequent research. Ince et al. (2016) used one-dimensional CNN to diagnose engine faults. This method does not need to fit discrete samples to obtain continuous functions and then perform orthogonal basis expansion, which has higher diagnostic accuracy. Jiang et al. (2019) automatically excavated the representative diagnostic information hidden in the original signal in the aircraft fault diagnosis, and to a certain extent got rid of the more complicated and difficult tasks such as manual feature extraction. Li et al. (2019) integrated deep learning technology into the fault diagnosis of 3D printers based on sub-optimal networks. The proposed pre-classification method can be used to adaptively determine the network structure parameters, and the fine classification method is adopted to improve the accuracy of fault diagnosis. Hu et al. (2019) took the planetary gearbox as the research object, and through the empirical mode decomposition of the vibration signal combined with the CNN for fault classification, it accurately and effectively realized the automation of the planetary gearbox fault diagnosis. Sun et al. (2016) used a sparse auto-encoder to automatically learn the inherent features in complex data, and the fault diagnosis effect was good. Wang (2019) combined the deep belief network with the auto-encoder and used it in the fault diagnosis of the bearing, which has higher robustness compared with the traditional method. Some scholars also pointed out that the process signals collected in the fault diagnosis process are converted into image signals through the mapping relationship and input into CNN to improve the accuracy of fault diagnosis (Chen and Yu 2020;

Zhu et al.2020).

The above research results show that deep learning has considerable advantages in fault detection and diagnosis, and the research on this topic has important reference significance. In the field of fault diagnosis of mine hoist, the hoist system is a unified whole coupled by multiple parts, and the braking system is particularly important. The faults of system units are interrelated, which threatens the safe operation of the whole machinery and equipment. The deep learning technology can effectively deal with the nonlinear strong coupling complex system. Therefore, this project uses CNN to train the fault data, establishes a fault diagnosis model, classifies common faults, and improves the efficiency of diagnosis and the accuracy of diagnosis.

2. The overall framework of fault diagnosis

The fault diagnosis studied in this paper involves four parts: data monitoring, processing, diagnosis and experimental verification. Among them, the diagnosis part is realized by CNN, and finally the fault diagnosis result is obtained. The fault diagnosis framework is shown in Fig.1.

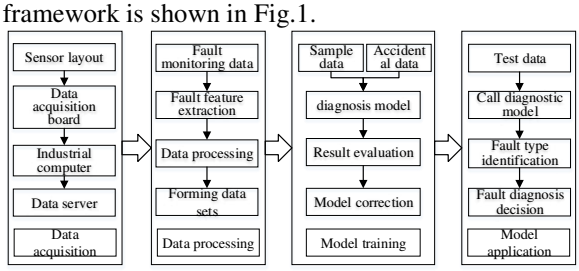


Fig.1 Fault diagnosis framework

(1) Data acquisition. The source of the data is mainly the data obtained by the monitoring system on the operating status of the hoist braking system and the data in the historical diagnosis knowledge base of the brake system.

(2) Data processing. Process the collected fault data of the hoist braking system, extract the fault characteristics, de-noise the data, calculate the feature quantity, process the missing values and continuous values of the sample data, and construct the training sample set and the test sample set.

(3) Model training. Establish a fault diagnosis model of the hoist braking system based on deep learning, classify the sample data, and continuously modify the model by evaluating the fault diagnosis results.

(4) Model application. The data is trained to obtain an algorithm model, thereby generating fault diagnosis rules, and judging the state of the braking system by classifying the data, which can be applied to the fault diagnosis of the hoist braking system.

3. Data collection and preprocessing

3.1 Failure mechanism analysis

The hoist braking system includes an actuator and transmission mechanism. The transmission mechanism is a hydraulic station to adjust and control the size of the braking torque. The actuator is a disc brake. The mine hoist uses a disc brake for braking. The braking force when the disc brake is closed is provided by several sets of disc springs. When the brake is released, the hydraulic station injects oil into the cylinder, and the oil pressure and the spring force offset, and then realize the release brake.

The main reason for the brake failure is that the braking torque is too small or too large. Too small braking torque will make the deceleration too small, resulting in excessive braking displacement, resulting in over-rolling phenomenon; excessive braking torque will cause the cage to stop at the scheduled location, excessive deceleration will cause excessive load on the wire rope, resulting in wire rope breakage. The calculation expression of braking torque is:

$$M_z = 2\mu N R_m n \tag{1}$$

Where M_Z represents the braking torque. μ represents the friction coefficient of the brake shoe to the brake disc, generally 0.3~0.35. R_m represents the average friction radius of the brake disc. n represents the number of hoist brake pairs. There are a large number of disc springs in the brake. After frequent use, it is easy to reduce the stiffness of the spring and reduce the braking force, which makes the brake ineffective. The expression of spring stiffness can be based on the mechanical relationship, and the following relationship can be obtained:

$$F_0 + k(\delta - b) - Ps - N = 0 \tag{2}$$

Where b represents the amount of wear of the brake shoe, and F_0 represents the closing spring force when the brake shoe is not worn, and k represents the spring stiffness coefficient. δ represents brake shoe clearance, P represents oil pressure, s represents piston area, and N represents brake positive pressure.

Among them, when $\delta > 0$ and $N = 0$, it is the brake release state; when $\delta = 0$ and $N > 0$, it is the closed state; when $\delta = 0$ and $N = 0$, it is the brake state.

If the cylinder resistance f is considered, then the formula (2) will be transformed into:

$$F_0 + k(\delta - b) - Ps - N = f \tag{3}$$

Among them, $f > 0$ represents the resistance during closing process; $f < 0$ represents the resistance during brake release.

According to formula (3), the change characteristics of various parameters under common fault conditions can be summarized, as shown in Table 1:

Table 1 Parameter variation law under different fault conditions

ID	Type of failure	Relational expression

1	Large hydraulic residual pressure	$F_0 - kb - P^{\uparrow}s - N^{\downarrow} = f$
2	Pressure loss of hydraulic station	$F_0 + k(\delta^{\approx 0} - b) - P^{\approx 0}s - N = f$
3	Insufficient spring stiffness	$\begin{cases} k^{\downarrow}(x_0 - b) - Ps - N^{\downarrow} = f, \text{closing brake} \\ k^{\downarrow}(x_0 + \delta^{\uparrow} - b) - Ps = f, \text{releasing brake} \end{cases}$
4	Severe wear of brake shoe	$F_0 - kb^{\downarrow} - Ps - N^{\downarrow} = f$
5	Hydraulic cylinder stuck	$\begin{cases} \frac{\partial N}{\partial P} \approx 0, \text{closing brake} \\ \frac{\partial \delta}{\partial P} \approx 0, \text{releasing brake} \end{cases}$

Note: x_0 is the pre-compression of the spring, $\uparrow$ means increase, $\downarrow$ means decrease.

3.2 Data monitoring and processing

From the above analysis, the brake shoe clearance, oil pressure, brake resistance are pressure, spring stiffness, spring pre-compression of displacement and deflection of brake disc are important parameters, decided to the running state of the brake system. Using these parameters can locate more typical and relatively simple fault phenomenon.

In order to diagnose more complex faults, the characteristic parameters of fault diagnosis are listed as shown in Table 2:

Table 2 Monitoring parameters of brake system

ID	Monitoring parameter	Unit
X1	brake disc yaw	mm
X2	brake gap	mm
X3	brake force	N
X4	oil pressure of hydraulic station	MPa
X5	oil pressure of releasing brake	MPa
X6	oil pressure of closing brake	MPa
X7	residual pressure of hydraulic station	MPa
X8	lifting speed	m/s
…	…	…

The above parameters are collected by sensors, then transferred to the fault diagnosis system. Since the magnitude and dimension of each parameter are different, if they are directly input to the neural network, the neural network may not converge, so they need to be unified under one scale. After all the data are processed, they are in the range of 0.04 to 0.98.

The first step of data processing is to restore the voltage signals and display them through the GUI user interaction interface. In the real-time monitoring process, there is noise in the measurement of the sensor, and there is also a certain randomness in the working condition of the hoist braking system, which may cause the sensor to fail to collect data or collect multiple data at a time during a certain sampling period. Therefore, it is necessary to de-redundant and de-damage the collected data. For outliers, this topic adopts the 3δ principle to choose; for incompleteness and redundancy, because the sampling period of sensor data collection is short and the amount of data acquired is large, the records with missing data can be deleted directly.

After the steps of de-redundancy and de-incompleteness, the data will be sampled, and 50 groups of data will be taken as a sample according to time stratification, and finally constitute the original data set. Since the number of feature parameters is 5, the size of each sample in the original data set is 5×50, and the two dimensions used to calibrate the data position are rows and columns, so the original data is a 2-dimensional array, which is also understandable It is a matrix, each row represents a characteristic parameter, and each column represents each data value at a different time. After the original data is encoded and processed, it is used as a CNN data set.

In order to make a reasonable diagnosis of several common failure phenomena and causes, this research builds a CNN to achieve this goal. An artificial neural network is connected in a specific way by multiple neurons with input and output capabilities, and the data input to the network is processed by the neurons through a learning algorithm and then output according to the designer's expectations. CNN is a feed-forward artificial neural network with deep structure that has the ability of representational learning and is built on the basis of biological vision, and includes convolution operations.

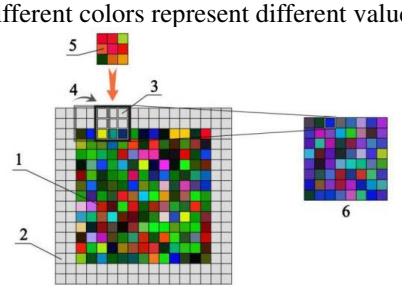
4. CNN-based deep learning algorithm

4.1 Algorithm idea

The CNN used in this topic consists of convolutional layer, pooling layer, fully convolutional layer, fully connected layer, output layer and Softmax layer.

(1) Convolutional layer

The convolutional layer is the core of the CNN and is the place where the neural network extracts abstract features from the data. The basic structure is shown in Fig.2. Each square represents an element, and different colors represent different values.



1. Input data; 2. Boundary expansion; 3. Receptive field; 4. Step size; 5. Convolution kernel; 6. Feature mapping

Fig.2 Structure of convolution layer

(2) Pooling layer

The role of the pooling layer is to reduce the network level of the data size according to certain rules under the premise of ensuring that the features extracted by the convolutional layer are not destroyed. The layer is divided into several small areas with a size of "m×n". For areas on the boundary that are not enough to make up "m×n", supplement it with 0. Common pooling operations include Mean pooling and Max pooling. This article uses Mean pooling.

(3) Fully convolutional layer

The function of the fully convolutional layer is to connect the "partially connected" layer and the "fully connected" layer in the network, so it has the characteristics of local connection and full connection at the same time. Its essence is a convolutional layer with no boundary expansion, the receptive field does not move, and the size is equal to the size of the entire input data.

(4) Fully connected layer

After the transition processing of the fully convolutional layer, the data is input to the fully connected layer, and the propagation method of this layer is similar to BP. In the convolutional network, the fully connected layer is equivalent to a classifier, which classifies the feature data obtained in the previous layers to obtain the output result of the network.

(5) Softmax layer

The Softmax layer is the last layer of the entire CNN. It is the layer where the network outputs the results of the operation. Its main function is to make each component in the output vector larger and smaller, and the sum of all components is 1. This is not only a process of normalization, but also a process of making the output result closer to the expected output. The operation principle of this layer is shown in Fig.3.

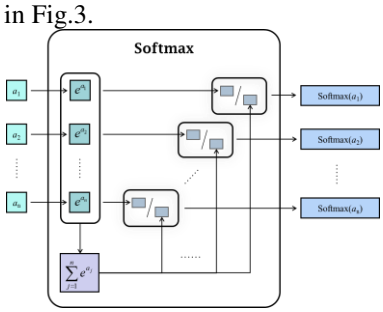


Fig.3 Operation principle of Softmax layer

Assuming that the number of components of the input vector of the Softmax layer is n, the vector is: $\mathbf{a} = [a_1, a_2, \Lambda\ , a_n]^T$. The algorithm of the Softmax layer is:

$$\mathrm{Softmax}(a_i) = \frac{e^{a_i}}{\sum_{j=1}^{n} e^{a_j}} \tag{4}$$

This topic uses the gradient descent method to train the neural network. The training process is as follows:

The expression of the cost function is:

$$C = \frac{1}{2}\sum_j \left(y_j - a_j^L\right)^2 = \frac{1}{2}\left(\mathbf{y} - \mathbf{a}^L\right)^{\mathrm{T}}\left(\mathbf{y} - \mathbf{a}^L\right) \tag{5}$$

The output error of the j neuron in the l layer:

$$\delta_j^l = \frac{\partial C}{\partial z_j^l} \tag{6}$$

Among them, the cost function is used to measure the gap between the actual output of the entire network and the expected output, that is, the error of the network. The so-called gradient descent method updates the weights and biases of neurons in the direction that reduces the cost function, so that the neural network converges to the desired output. The expression is:

$$\Delta w_{jk}^l = -\eta \frac{\partial C}{\partial w_{jk}^l}, \quad \Delta b_j^l = -\eta \frac{\partial C}{\partial b_j^l} \tag{7}$$

Where η is the learning rate, usually a real number less than l to adjust the weight and the step size of the bias update. In the training process of the neural network, the parameter update is based on the error, and the update amount for the first layer parameter is:

$$\Delta \mathbf{W}^l = \eta \boldsymbol{\delta}^l (\mathbf{a}^{l-1})^{\mathrm{T}}, \quad \Delta \mathbf{b}^l = \eta \boldsymbol{\delta}^l \tag{8}$$

Errors are the basis for updating network parameters, and errors can propagate layer by layer along the network structure, so the network parameters can be updated layer by layer. In the CNN, the Softmax layer is the last layer, and the output of the network is:

$$y_i = \mathrm{softmax}(a_i), i = 1,2,\mathrm{K}\ ,n\ , \tag{9}$$

The error propagation formula of Softmax layer is:

$$\delta_k^a = \sum_{i=1}^{n} \delta_i^y \frac{\partial y_i}{\partial a_k} = \frac{e^{a_k} \sum_{j=1}^{n} (\delta_k^y - \delta_j^y) e^{a_j}}{(\sum_{p=1}^{n} e^{a_p})^2} \tag{10}$$

Since there are no neurons in the Softmax layer and the pooling layer, there is no problem of weight and bias update. The recursive relationship of the error back propagation of the full convolutional layer is:

$$\delta^a = \sum_{m=1}^{n} \delta_{m\,m}^z K \tag{11}$$

The update principle of the full convolution

kernel and its bias is consistent with the update principle of the convolution kernel and its bias in the convolutional layer, and will not be repeated here.

4.2 Data encoding method

Because CNN has outstanding performance in processing images, it is necessary to standardize the original data and encode it into an image-like form, essentially mapping the original data set samples represented by a two-dimensional array to the training set represented by a three-dimensional array (hereinafter collectively referred to as CNN data set). The specific approach is as follows:

The coded sample size is 50×50×5, which is a three-dimensional array with 50 rows, 50 columns, and 5 layers. For a sample in the CNN data set, its number of layers corresponds to the number of rows in the original sample set, and its number of columns corresponds to the number of columns in the original data set. Therefore, the essence of the encoding process is to place the first sample in the original data set. The quantity in the $j-th$ column of the i row is mapped to each row of the $j-th$ column of the $i-th$ layer of the CNN data, as shown in Fig.4.

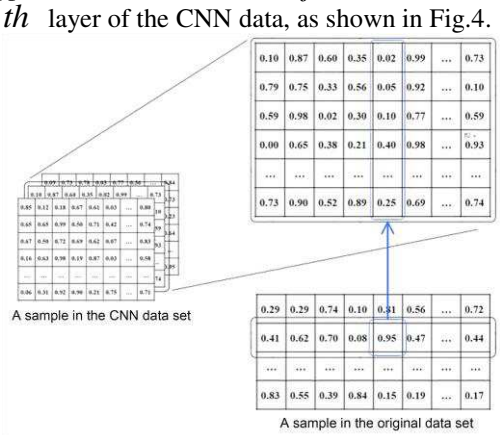


Fig.4 Coding principle of CNN data

In Fig.4, the element "0.95" in the second row and fifth column of a sample in the original data set is mapped to the second layer and fourth column of the corresponding sample in the CNN data. The mapping method is as follows:

For a certain data $\tilde{x}$ in the original data set, the above mapping process actually maps this data into a column vector $X=[x_1 \quad x_2 \quad \mathrm{K} \quad x_{50}]^{\mathrm{T}}$. The relationship between data $\tilde{x}$ and vector X is as follows:

$$50\tilde{x}=\sum_{i=1}^{50} i x_i \tag{12}$$

The method of determining each component in vector X is as follows:

For a certain data $\tilde{x}$ in the original data set, round it to the nearest unit of 0.02, and record the result as $p=\mathrm{round}(50\tilde{x})$. Then assign the p-th component x_p of the vector X to 0.5, and assign the two adjacent components to $0.25-b$ and $0.25+b$, where b is the undetermined coefficient, and the other components are assigned a value of 0, as shown in Fig.5:

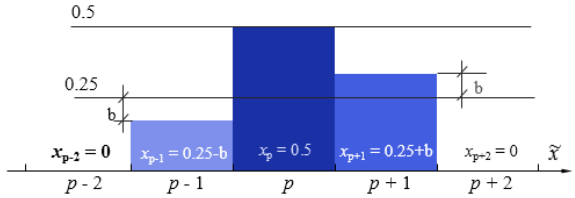


Fig.5 Component assignment

The above assignment result should satisfy formula (12), namely:

$$\begin{aligned}50\tilde{x} &= \sum_{i=1}^{50} i x_i \\ &= 1\times 0+\mathrm{K}+(p-1)\left(\frac{1}{4}-b\right) \\ &\quad + p\times\frac{1}{2}+(p+1)\left(\frac{1}{4}+b\right)+\mathrm{K}+50\times 0 \\ &= p+2b\end{aligned} \tag{13}$$

From this, the value of b can be derived.

$$b=\frac{50\tilde{x}-p}{2} \tag{14}$$

For example, when a certain data $\tilde{x}$ in the original data set is 0.732, there are:

$$p=round\,(50\times 0.732)=round\,(36.6)=37$$

$$b=\frac{50\times 0.732-37}{2}=-0.2$$

$$\begin{cases} x_{36}=0.25-(-0.2)=0.45 \\ x_{37}=0.5 \\ x_{38}=0.25+(-0.2)=0.05 \\ x_{\text{其他}}=0 \end{cases}$$

$$X=[0 \quad 0 \quad \mathrm{K} \quad 0 \quad 0.45 \quad 0.5 \quad 0.05 \quad 0 \quad \mathrm{K} \quad 0]^{\mathrm{T}}$$

Through the above method, the samples in the original data set can be mapped to the CNN data set.

5. Algorithm analysis and improvement

When the neural network training samples are small, the following situation may occur: the neural network has very small errors in the calculation of the training samples, but the errors of the samples that have not participated in the training (including the test samples) are relatively large. This phenomenon is called "over-fitting" and is a common problem in machine learning. Hinton et al. (2012) proposed the dropout method to solve such problems. In each training process, he makes the neurons in the network stop working according to the (very small) probability p. If there are N neurons in this layer, there will be Np neurons not participating in the training in this training. Due to the randomness of dropout, the complex "co-adaptation" relationship of some neurons in the network due to insufficient training samples will be destroyed, and the trained neural network will have a better potential to face unknown

data. Based on this, this paper proposes the CNN dropout improvement method as follows:

The error obtained by back-propagation can calculate the change of the weight (or bias) to be updated. In order to achieve dropout, the actual change of the weight (or bias) is different from the calculated change. The specific manifestation is that individual elements have a great attenuation, that is, during the update process, the amount of change of some neurons is close to 0, as if they have been discarded.

The activation probability of each neuron is:

$$p(r) = \max(0, \min(1, \frac{r-\alpha}{\beta-\alpha})) \tag{15}$$

Where α is drop point, β is the reserved point, Function $p(\cdot)$ is called "linear dropout function". Its characteristics are: when the random number is less than the discarding point α, $p(r)=0$; when the random number is greater than the reserved point β, $p(r)=1$; when the random number is between the two, it will be linearly mapped between 0 and 1, as shown in the Fig.6.

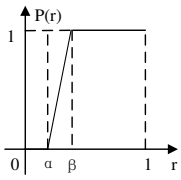


Fig.6 Linear dropout function

6. Experimental verification

6.1 Verification process

Take the laboratory 2JTP-1.2 type hoist as the test object to test and verify the diagnostic model generated by the algorithm. The test object is shown in Fig.7.

(a)Hoist (b)Brake (c)Hydraulic system

Fig.7 Test object

In order to test the accuracy and superiority of CNN in the fault diagnosis of mine hoist brake system, this section uses BP as the control group, and compares two different neural networks with the same sample. Select the brake shoe displacement, spring force, oil pressure and brake disc deflection as the network characteristic parameters to diagnose the fault phenomena, which includes normal (F0), excessive residual pressure(F1), pressure loss of hydraulic station(F2), spring failure of closing brake(F3), spring failure of releasing brake(F4),severe wear of brake(F5),excessive deflection of closing brake(F6),excessive deflection of releasing brake(F7).

The test samples are derived from the fault simulation experiment. The simulation experiment uses Table 1 as the theoretical basis to simulate the various faults respectively. For the specific simulation method, please refer to the paper published by the research group (Li et al.2020). After de-redundancy, standardization and coding of the signals collected by the sensors, the test set used to verify the neural network used in this subject is obtained.

Table 3 is an example of BP test samples, and Fig.8 is an example of CNN test samples after encoding.

Table 3 Sample examples of BP

ID	X1	X2	X3	X4	X5	X6	X7	X8
1	0.615	0.877	0.020	0.023	0.068	0.988	0.681	0.025
2	0.617	0.877	0.355	0.030	0.064	0.987	0.135	0.020
3	0.615	0.876	0.990	0.028	0.069	0.990	0.225	0.023
4	0.612	0.020	0.052	0.025	0.020	0.988	0.840	0.026
…	…	…	…	…	…	…	…	…

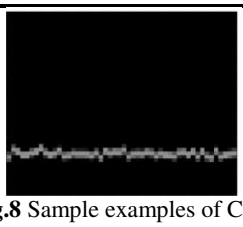


Fig.8 Sample examples of CNN

In Table 3, X1 represents the displacement of closing brake, X2 represents the spring force of closing brake, X3 represents the oil force of closing brake, X4 represents the wear of closing brake, X5 represents the displacement of releasing brake, X6 represents the spring force of releasing brake, X7 represents the oil force of releasing brake, X8 represents the wear of releasing brake.

The size of the CNN data is 50×50×5. Fig.8 shows one of the layers. The darker the square, the smaller the value of the element in the corresponding matrix. The test samples are sequentially input into the trained neural network, and after forward propagation, the comparison operation result is consistent with the expected result. If they are consistent, it is recorded as "correct", otherwise it is recorded as "error". The test results of the BP and CNN are shown in Fig.9 and Fig.10, respectively, where each point represents a sample, red means the diagnosis is wrong, and black means the diagnosis is correct.

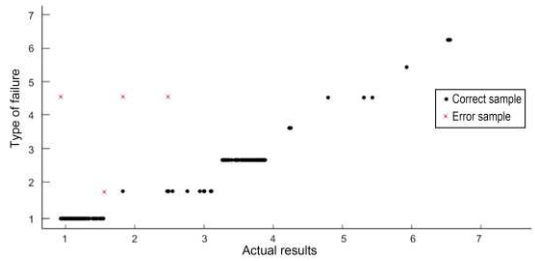


Fig.9 Test results of BP

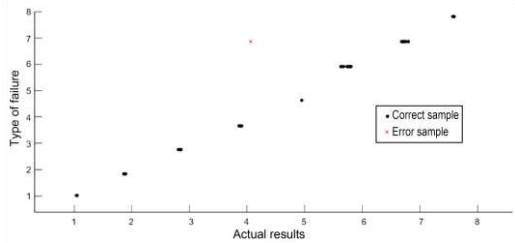


Fig.10 Test results of CNN

6.2 Result analysis

By comparing Fig.9 and Fig.10, it can be seen that the distribution of each type of sample in the CNN test result is more compact than that of the BP neural network, which shows that CNN has higher advantages in sample classification and recognition. In addition, by calculating the percentage of correct samples in all samples, the correct rate of the model can be calculated to measure the accuracy of the model, as shown in Table 4.

Table 4 Accuracy of fault diagnosis

network class	number of faults involved	number of test sets	accurate rate （%）
BP	7	35	71.4286
CNN	4	40	95
	6	60	95
	7	160	99.375
	8	90	98.75

It can be seen that the BP neural network is not as accurate as CNN in the diagnosis of hoist brake system faults, but during the CNN training process, normal samples will be involved with other samples, resulting in diagnosis errors, that is, CNN has higher requirements for the consistency of fault samples. If the number of fault samples increases and different types of fault parameters are involved or contradictory, the diagnostic accuracy of the network will decrease. It can also be seen from Table 4 that after removing the samples in the normal state, the accuracy of CNN has increased from 98.75% to 99.375%.

6.3 Diagnostic accuracy analysis

Next, the theoretical correctness analysis of the fault type of serious brake shoe wear selects 100 samples. When the brake shoe wear is severe, the brake shoe displacement for closing will increase significantly, and the closing spring force will decrease significantly, as shown in Fig.11.

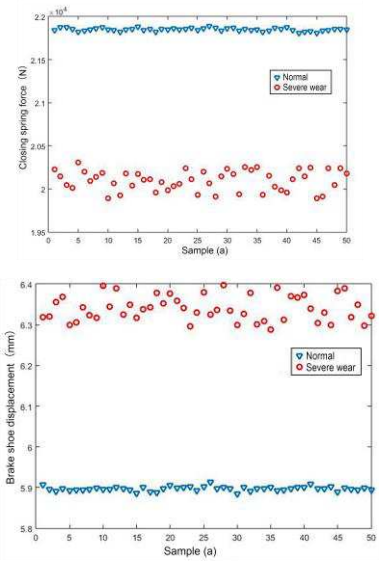


Fig.11 Parameter comparison of normal condition and brake shoe wear

It can be seen that the possibility of serious brake shoe wear caused by excessive brake shoe clearance is high. In order to verify the correctness of the results, the following analysis is made based on the monitoring data:

During the braking process of the hoist, the residual pressure of the brake oil and the friction coefficient are within the normal range. According to the data of the brake shoe displacement, the brake shoe displacement curve is drawn, as shown in Fig.12. It can be seen from the figure that the brake shoe gap exceeds the limit, and it is judged that the fault may be caused by the brake shoe gap being too large, and the brake shoe gap needs to be adjusted.

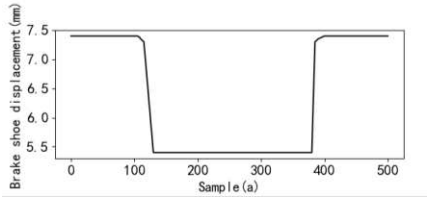


Fig.12 Brake shoe displacement curve

This is consistent with the failure mechanism described above, and the results of using CNN to classify the failure are shown in Fig.13. Among them, the blue sample is a normal sample identified by CNN, and the red sample is a serious brake shoe wear sample identified by CNN.

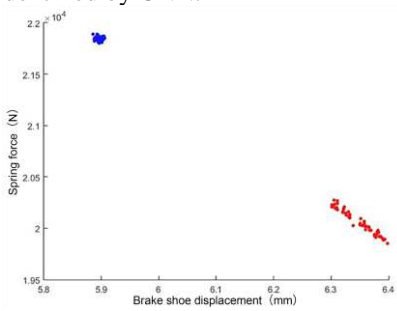


Fig.13 Test results of CNN theory correctness

It can be clearly seen that CNN divides the

samples into two categories, which is consistent with the failure mechanism described above, which also shows that CNN has a certain theoretical correctness.

7. Conclusion

In this paper, a CNN mine hoist braking system fault diagnosis method is proposed, and detailed theoretical analysis and comprehensive experimental are carried out. The main work and conclusions are as follows.

(1) A data encoding method is proposed to convert the one-dimensional signal collected by the sensor into a two-dimensional image. The original data set samples represented by the two-dimensional array are mapped to the training set and the test set represented by the three-dimensional array, which increases the efficiency and reliability of information transmission.

(2) Using the improved CNN for fault diagnosis can get 99.375% accuracy. Compared with BP, it has better robustness and accuracy and adaptability to complex samples.

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