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A research on state monitoring of transformer based on deep learning

Peng-cheng Ji[1], ShuoLiu[2], Chen-ran Fu[3], Shi-yaoLi[4]
[1](School of Control and Computer Engineering, North China Electric Power University, Beijing 102206,China)
[2](School of Control and Computer Engineering, North China Electric Power University, Beijing 102206,China)
[3](School of Control and Computer Engineering, North China Electric Power University, Beijing 102206,China)
[4](School of Control and Computer Engineering, North China Electric Power University, Beijing 102206,China)

Abstract: Based on the deep learning method, a feature reduction method of state monitoring index based on autoencoder network is first proposed, and then a convolution neural network state monitoring classification model is built. The feature vectors of dimensionality reduction generated by autoencoders are used as input of convolution neural network, and the multi classifier of transformer state is realized through convolution neural network classifier. The test of the monitoring data of the transformer of the proposed method using test results prove the correctness and effectiveness of the feature reduction method based on auto encoder, also proved the effectiveness of the convolutional neural network state monitoring classification model based on classification performance is better than that of SVM and MLP.

Keywords: state monitoring; autoencoder; convolution neural network; transformer

I. INTRODUCTION

The health of the substation determines whether the grid can operate normally and stably, especially transformers. If the transformer fault detection is not timely, it will bring great losses to the power system [1]. Therefore, accurate and efficient condition monitoring of the transformer is especially important. Improving the stability and reliability of the transformer operation can greatly improve the reliability of the operation of the power grid.

Transformer condition monitoring methods are divided into traditional state monitoring methods and intelligent state monitoring methods. The traditional method is regular maintenance, the on-duty personnel judge the presence or absence of abnormality by patrolling the appearance of the transformer and indicating instruments, etc., so as to avoid accidents [2]; intelligent methods mainly include expert systems, support vector machines, and extreme learning. Machine, neural network and other methods. The intelligent state monitoring method further improves the accuracy of transformer fault detection, but there are different degrees of limitations. The vast amount of empirical knowledge required by the expert system is difficult to obtain; the neural network will fall into local optimum; although the support vector machine can overcome the over-fitting problem, it is a two-classification algorithm; although ELM has a fast training speed, the training model The stability is poor. In addition, the existing transformer condition monitoring method is not suitable for sample training of large data volume, and has high requirements for sample completeness, low utilization rate for unlabeled samples, and limited learning ability. The detection accuracy needs to be treated. Improve [3].

In view of the existing problems of the existing transformer state monitoring method, this paper applies the deep learning method to transformer condition monitoring. Firstly, a feature reduction method based on self-encoding network is proposed, which reduces the transformer index system and reduces the input eigenvalues of the late state classification model. Then, a CNN condition monitoring classification model is constructed, and the model outputs multi-classification results in the form of probability. The training and testing of a large number of unlabeled data measured by transformers prove that the method can effectively solve the problem of transformer state monitoring classification and improve the accuracy of state detection [4]. And this paper compares and analyzes the condition monitoring classification methods based on SVM and MLP.

II. DEEP LEARNING METHODS INTRODUCTION

The deep learning network structure is a deep nonlinear neural network [5]. The deep and shallow learning algorithms are different because the deep learning algorithm can realize the layer-by-layer transformation of features and better representation complexity using a simple network structure. The approximation of the function. The deep learning structure is equivalent to a multi-layer neural network model, and contains multiple hidden layer perceptrons. This feature makes the feature data learned by the deep learning model more representative and more representative of the original data, which will be more conducive to visualization problems. And classification issues.

2.1Autoencoder

The autoencoder network proposed by Hinton is a feedforward and non-returning neural network, which reproduces the neural network of the input signal as much as possible. At the same time, the number of hidden layer nodes is less than input nodes, so the purpose of data dimensionality reduction can be achieved. As shown in Figure 1, the autoencoder network structure diagram. The autoencoder consists of three layers: the input layer, the hidden layer and the output layer. The hidden layer can have multiple layers in the input layer [6], and an excitation function is used to map between layers.

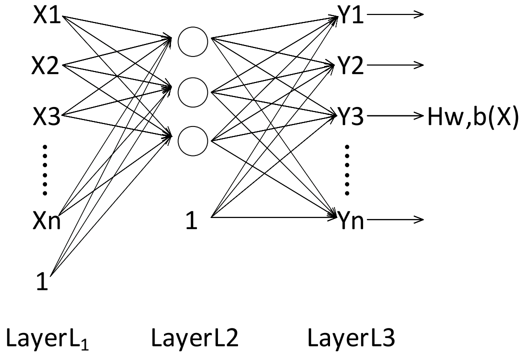

Figure 1: Autoencoder network structure diagram

As shown in Figure 2,The data reduction process of the autoencoder consists of three steps, which are the pre-training process, the unfolding process and the fine-tuning process [7]. When the autoencoder reduces the data, it firstly obtains the corresponding initial weight by pre-training and unfolding, and then obtains the optimal weight by fine-tuning the initial weight. After encoding and decoding, the compressed low-dimensional data can be obtained. Replace the original high-dimensional data. In the aspect of autoencoder network parameter training, the backpropagation method is used for training, the trouble is a large number of training samples are needed, and as the network structure becomes complicated, the computation explodes.

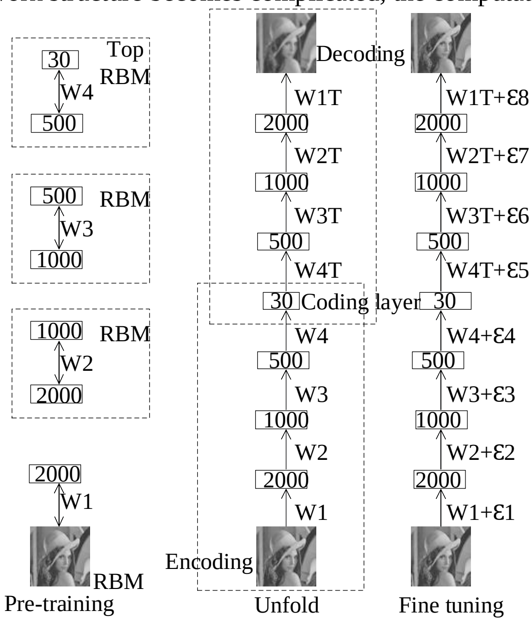

Figure 2 Autoencoder reduction process

(1)The pre-training and unfolding process of the autoencoder can be seen as a forward compression operation and a reverse expansion operation from the data. The weight formula is updated in the weight training adjustment process as follows:

$$\Delta\omega_{ij} = \frac{\eta}{T}(\langle v_i h_j \rangle^{+} - \langle v_i h_j \rangle^{-}) \quad (1)$$

Where: T is the network temperature; η is the learning rate, $\langle v_i h_j \rangle^{+}$ is the positive average correlation; $\langle v_i h_j \rangle^{-}$ is the reverse average correlation. The pre-training times are set in advance, and the network performs layer-by-layer learning, and the initial weight is obtained through the pre-training process.

(2)Fine-tuning is using the initial weights obtained by the pre-training and adjusting the weights to achieve the optimal reconstruction effect. The high-dimensional data is input to the encoder to obtain low-dimensional data, and the reconstructed data is obtained after being decoded by the decoder. The fine-tuning process allows low-dimensional data to represent high-dimensional data more accurately, thus mapping valid features in high-dimensional data to low-dimensional data.

The encoder gets the encoded data as follows: $\mathrm{h}_n = Cf(x_n)$ (2)

The reconstructed data obtained by the decoder is as follows: $r = Sf(h_n)$ (3)

In general, the method of adjusting the weight of the fine-tuning process is adjusted by backpropagating the reconstruction error. The cross entropy loss function is generally selected, and the weight is adjusted by the reconstruction error to obtain the optimal weight. The formula is as follows:

$$L(x,\ \gamma) = -\sum_{i=1}^{d_x} x_i \log(\gamma_i) + (1-\gamma_i)\log(1-\gamma_i) \quad (4)$$

2.2 Convolutional neural network (CNN)

In 1998, LeCun et al. proposed a BP neural network for training CNN based on neurocognitive machines [8]. As shown in FIG. 3, the four stages of the basic structure division of the CNN are: input stage, first feature mapping stage, second feature mapping stage, and classification stage. All feature maps form a feature extractor, which is a superposition of several convolution layers and several sub-sample layers. The CNN has a good a priori structure between the neurons in each layer. It is a local connection. Several feature mapping surfaces of a convolutional layer contain several neurons. These neurons share weights and share weights. Reducing the complexity of CNNs can improve feature extraction efficiency while reducing the complexity of data reconstruction during feature extraction and classification. If all the parameters of the CNN settings are appropriate, then a more effective training effect will be obtained.

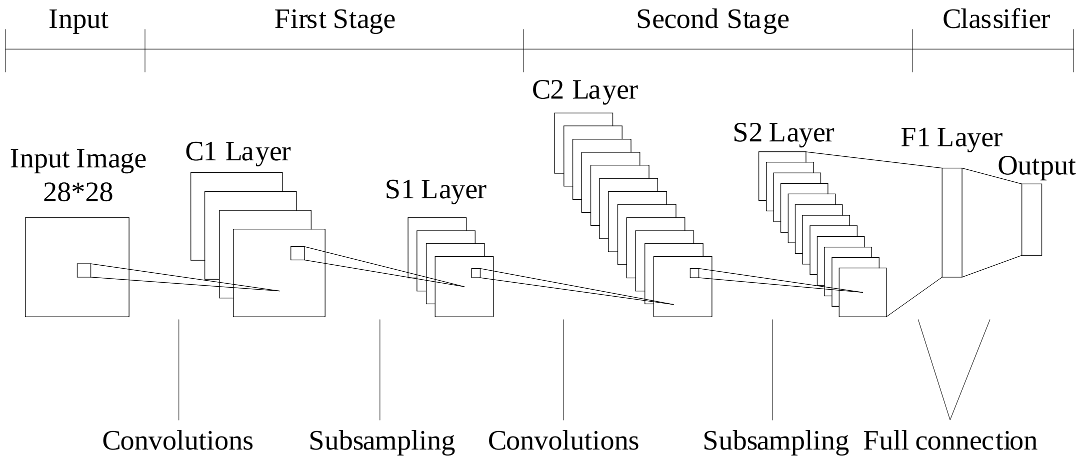

FIG. 3 basic structure of convolutional neural network

CNN training process is mainly divided into two parts: forward and backward propagation [9]:

(1) Forward propagation process. A sample(X,Y_P) is randomly selected, where X is the input to the CNN and Y_P is the expected output of the product neural network. When X is entered, the layer calculation propagation can be calculated according to the following formula:

$$\mathrm{O}_P = F(\cdots(F_2(F_1(XW_1)W_2)\cdots)W_n) \quad (5)$$

(2) Backward propagation process. This process is the process of error back propagation, calculating the difference between the actual output and the expected output:

$$E_P = \frac{1}{2}\sum_j (y_{pj} - \mathrm{o}_{pj})^2 \quad (6)$$

The matrix of the connection weights is updated by minimizing the error to optimize the target.

III. FEATURE EXTRACTION BASED ON AUTOENCODER

3.1Transformer indicator selection

The number of states that can be monitored to effectively reflect the operating conditions of the transformer is also increasing, the monitoring results are more and more accurate, and the utility is more practical, and the state monitoring of the transformer also reflects whether the running performance is good. To use the state monitoring quantity to accurately classify, evaluate and predict the transformer, it is necessary to establish a scientific and reasonable state monitoring quantity index system, as shown in Figure 4, the indicator system of the transformer.

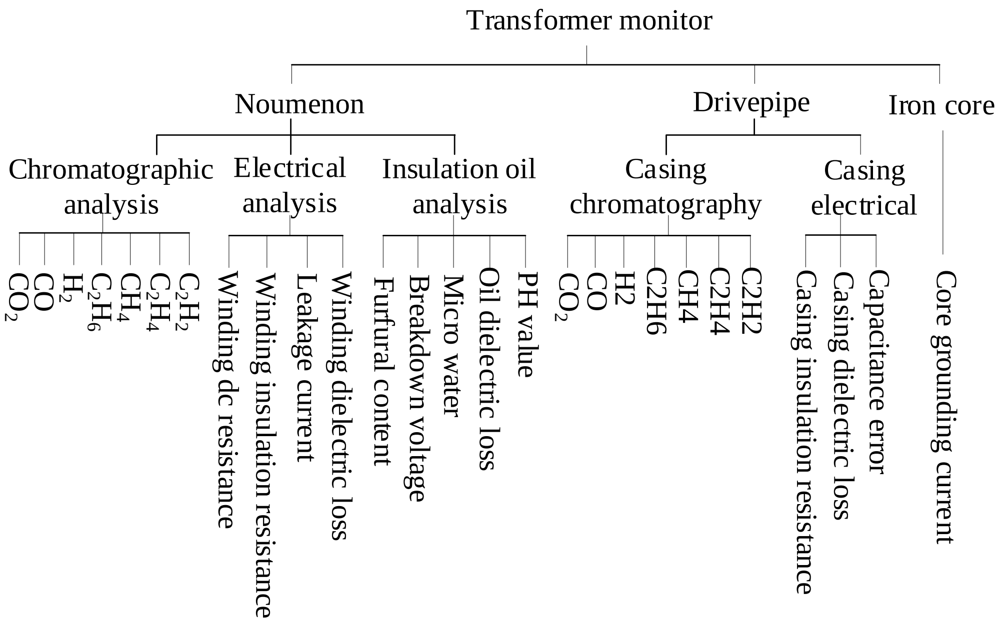

FIG. 4 transformer index system

As shown in Table 1, each transformer data sample indicator. In order to obtain accurate condition monitoring results, each sample is normalized and normalized before it can be used as an input. In this paper, we use the scale transformation method to normalize the sample data. The formula used is:

$$z = \frac{y - \min(y)}{\max(y) - \min(y)} \quad (7)$$

Where: $\min(y)$ and $\max(y)$ are the minimum and maximum values of the same indicator data ; y is the original input data; z is the normalized data.

Table 1 sample indexes of transformer data

Serial number	**Item**	**Pointer type**
01	Noumenon chromatography-C_2H_2	Cost indicator
02	Noumenon chromatography- C_2H_4	Cost indicator
03	Noumenon chromatography-CH_4	Cost indicator
04	Noumenon chromatography- C_2H_6	Cost indicator
05	Noumenon chromatography- H_2	Cost indicator
06	Noumenon chromatography- CO	Cost indicator
07	Noumenon chromatography- CO_2	Cost indicator
08	Winding dc resistance	Efficiency indicators
09	Winding insulation resistance	Efficiency indicators
10	Leakage current	Cost indicator
11	Winding dielectric loss	Cost indicator
12	Micro water	Cost indicator
13	Dielectric loss of oil	Cost indicator

14	Furfural content	Cost indicator
15	Breakdown voltage	Efficiency indicators
16	PH value	Cost indicator
17	Casing chromatography-C2H2	Cost indicator
18	Casing chromatography-C2H4	Cost indicator
19	Casing chromatography- CH_4	Cost indicator
20	Casing chromatography- C_2H_6	Cost indicator
21	Casing chromatography- H_2	Cost indicator
22	Casing chromatography- CO	Cost indicator
23	Casing chromatography- CO_2	Cost indicator
24	Casing insulation resistance	Efficiency indicators
25	Casing dielectric loss	Cost indicator
26	Capacitance tolerance	Efficiency indicators
27	Core grounding current	Cost indicator

3.2Feature extraction based on Autoencoder

The autoencoder network structure includes the input layer and the output layer as well as the hidden layer in the middle, and the number of layers of the hidden layer determines the nonlinear complexity of the network structure [10]. Depending on the number and complexity of the monitoring indicators, 3 to 5 layers of hidden layers are generally used. For the 27 indicators in the indicator system, this paper selects the 5-layer autoencoder network structure, which includes 3 layers of hidden layers to represent the nonlinear relationship between the data. For the index data of the 27-dimensional transformer, the autoencoder can reduce the dimension to the data of the number dimension required by the corresponding application. This article will input high-dimensional data dimensionality output to 5D data, as shown in Figure 5.

3.3Analysis of feature extraction results

Using simulation data to simulate the historical data of a transformer for a certain period of time as a sample, 1000 samples were selected, 700 were used as training samples, and the remaining 300 were used as test samples. In order to significantly reduce the complexity of the subsequent establishment of the state monitoring classification model, the autoencoder network structure designed in this experiment nonlinearly maps 27-dimensional eigenvalues into 5-dimensional space.

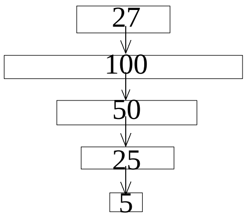

FIG. 5 Autoencoder dimension reduction network structure

The experiment selects the Mean Squared Error (MSE) to represent the difference between the reconstructed data and the original data. The MSE definition is as follows:

$$MSE = \frac{1}{n}\left(\sum_{i=1}^{27}(x_i - x_i')\right)^2 \quad 俥 \qquad (8)$$

Where: n is the size of the sample, x_i is the eigenvalue of the indicator, and x_i' is the reconstructed eigenvalue

In the experiment, the number of iterations is set to 200. According to the experimental results, as shown in Figures 6 and 7, it can be seen that after 50 iterations, the reconstruction error tends to a stable value. Figure 6 shows the RBM per layer during the pre-training process. Reconstruction error of the network map. Figure 7 shows the reconstruction error of the trimming process.

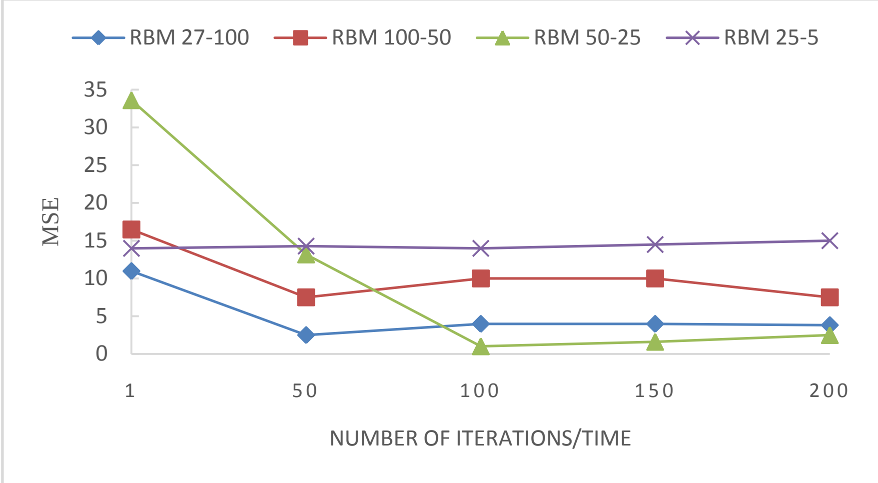

FIG. 6 reconstruction errors of RBM pre-training

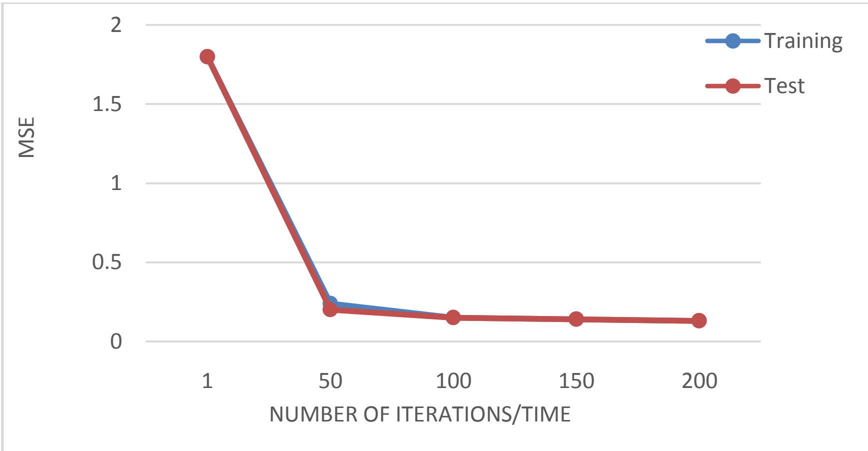

FIG. 7 reconstruction error of fine-tuning process

In order to fully evaluate the performance of the autoencoder and the conventional dimensionality reduction method in data dimension reduction, this paper compares the average reconstruction error of the autoencoder and PCA. Using the autoencoder and PCA to reduce the measurement data to the same dimension, that is, the PCA and the autoencoder can obtain the average reconstruction error by fine-tuning the 200 training process and the test process. By comparing the reconstruction errors of the two dimensionality reduction methods, the advantages and disadvantages of the two methods are obtained. The autoencoder and PCA average reconstruction error is shown in Table 2.

Table 2 mean reconstruction errors of Autoencoder and PCA

Dimension	Autoencoder		PCA	
	Train MSE	Train MSE	Train MSE	Train MSE
5	3.26e+00	3.28e+00	4.74e+00	9.17e+00
10	3.26e+00	3.27e+00	9.42e+00	1.83e+01
15	3.26e+00	3.29e+00	2.73e+01	1.41e+03
20	3.27e+00	3.31e+00	1.87e+03	3.64e+03

The autoencoder can reconstruct the original high-dimensional data into low-dimensional data, and these low-dimensional data can fully represent the original high-dimensional data, and according to the obtained training MSE and test MSE. It can be seen from Table 2 that there is a clear advantage compared with the training MSE and the test MSE obtained by the PCA dimensionality reduction method.

IV. CNN MONITORING CLASSIFIER

4.1CNN based classification model construction

The integrated dimension CNN constructs a classifier using the Softmax activation function at the output layer, and a state monitoring classification model based on CNN can be obtained. The function of this classification model is to input a comprehensive eigenvalue reduced by the autoencoder, and after several convolutional and downsampling layers, it is fully connected to the Softmax classifier to output an N*1 classification matrix value. Where N represents the number of multiple classifications. As shown in FIG. 8, the feature extraction parameters of the substation equipment state monitoring classifier model based on the integrated dimensional CNN are obtained through the training data set, thus avoiding the extraction of artificial features. Moreover, weight sharing can achieve parallel training and calculation, which greatly improves the computational efficiency of the classifier [11-18]

4.2 Transformer condition monitoring overall model

In this paper, a CNN condition monitoring classifier model is constructed. As shown in Fig. 9, its input is the feature vector after the dimensional reduction by the autoencoder. After the CNN condition monitoring classifier convolution and subsampling, the whole is performed. Connected, the transformer state is multi-classified by the Softmax classifier, and the classification result is expressed in probability form.

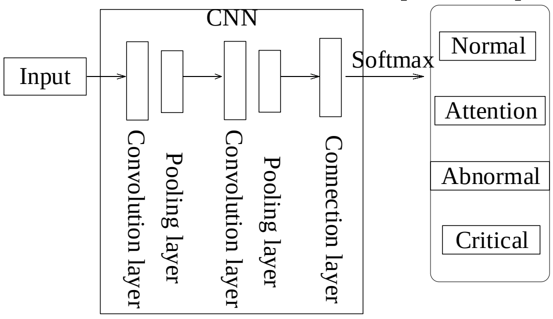

FIG. 8 classifier model architecture of comprehensive dimensional CNN

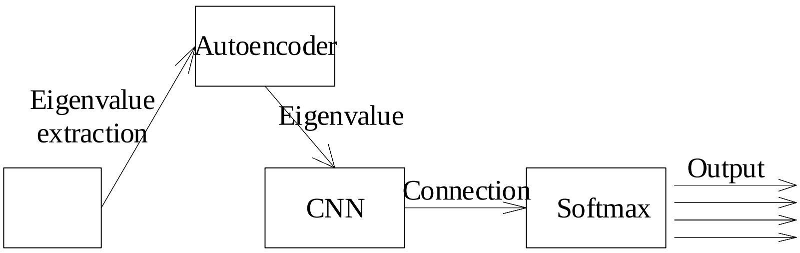

FIG. 9 The model of transformer state monitoring

4.3 Implementation of Transformer Condition Monitoring Method Based on AE-CNN-Softmax

The implementation process of transformer state monitoring method based on AE-CNN-Softmax is as follows:

(1) Select sample data, normalize the sample data, and divide it into training set and test set according to a certain proportion.

(2) Feature extraction is performed on the sample data using the Autoencoder algorithm.

Step 1: Parameter initialization. The initial number of iterations is set to t=0, and the maximum number of iterations for pre-training and fine-tuning is 200. Set the autoencoder to a 5-layer network structure.

Step 2: Pre-training. The processed sample data is taken as an input, and after reaching the maximum number of iterations, a 5-dimensional eigenvalue is obtained. The eigenvalue after the dimension reduction is not a specific physical index, but basically represents the original 27-dimensional indicator data.

Step 3: Fine tune. In order to minimize the reconstruction error, the cross-entropy function is used to adjust the pre-training to obtain the initial weight. If the maximum number of iterations is reached, the final result is obtained, otherwise the iteration continues.

(3) Establish a transformer state monitoring model based on CNN

(a) Initialize all weights;

(b) For each layer of network loop iteration:

Loop iteration for each sample in the dataset:

FP: forward from the input layer to the output layer, you can find the output of each neuron in each layer;

BP: Calculate the incremental error at the output layer and propagate it back to a hidden layer to calculate the incremental error as ;

PP: Post-processing to calculate the derivative of the error for weights and offsets.

Update: update the weight and offset with the partial derivative calculated in the post-processing, the learning rate is :

$$w_{ik}^{l-1}(t+1) = w_{ik}^{l-1}(t) - \varepsilon \frac{\partial E}{\partial w_{ik}^{l-1}} \quad (9)$$

$$b_k^l(t+1) = b_k^l(t) - \varepsilon \frac{\partial E}{\partial b_k^l} \quad (10)$$

V. ENGINEERING CASE ANALYSIS

The measurement data in the experiment, from the actual monitoring data of the substation from December 2016 to April 2017, the data sampling interval is 20 minutes, more than 10,000 pieces of available data of the transformer, first select 8000 pieces of data from the transformer to train the model proposed in this paper. Secondly, the data from January 1 to January 31 is used to verify the validity of the model, including 2000 available data of the transformer. Some experimental data are displayed, as shown in Table 3.

Table 3 transformer experimental measurement data

Serial number	T_1	T_2	···	T_{9999}	T_{10000}
01	0.06	0.05	···	0.06	0.06
02	0.3	0.4	···	0.3	0.5
03	0.8	0.8	···	0.9	1.0
04	0.6	0.7	···	0.5	0.9
05	2.1	2.5	···	2.8	3.2
06	25	26	···	32	32
07	51	52	···	65	69
08	680	691	···	726	728
09	867	872	···	882	900
10	0.5	0.6	···	0.8	0.8
11	11%	12%	···	13%	14%
12	10	10	···	10	10
13	1%	1.3%	···	1.4%	1.7%
14	0.042	0.042	···	0.043	0.043
15	45	46	···	44	47
16	0.05	0.05	···	0.06	0.06
17	0.20	0.20	···	0.22	0.22
18	0.5	0.5	···	0.6	0.6
19	21	21	···	22	22
20	1.6	1.6	···	1.8	1.8
21	80	8	···	83	83
22	23	23	···	28	28
23	44	44	···	48	48
24	1200	1203	···	1215	1218
25	0.3%	0.3%	···	0.4%	0.4%
26	0.8%	0.9%	···	1.0%	0.8%
27	0.13	0.13	···	0.15	0.15

(1) Validity based on AE-CNN-Softmax condition monitoring classification method

In order to comprehensively compare the superiority of the proposed AE-CNN-Softmax state monitoring classification method, 10,000 measurement samples of transformers were selected as experimental data, and the training and test sample sets were composed in a ratio of 4:1. The ROC curves for transformer condition monitoring are shown in Figures 10 and 11, respectively.

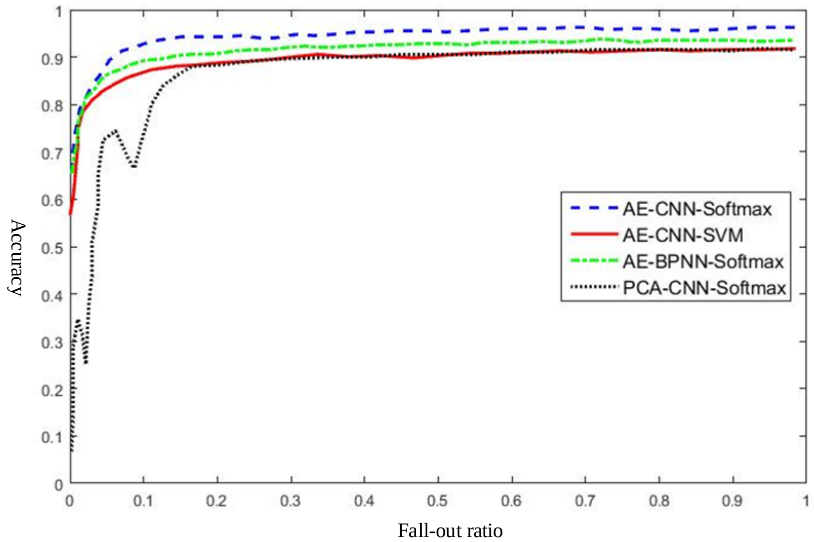

Figure 10 ROC curve of training model applied to transformer sample data

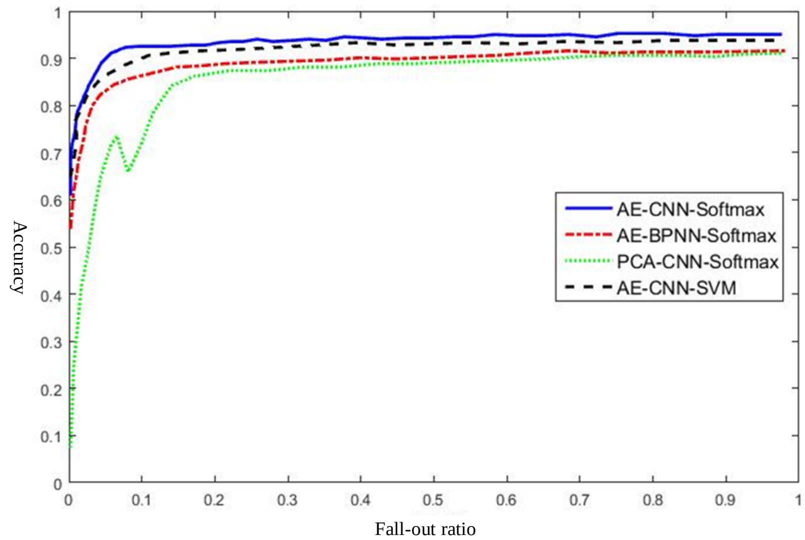

Figure 11 ROC curve of the model tested in transformer sample data

It can be seen from Fig. 10 and Fig. 11 that the method proposed in this paper can accurately detect the abnormal data of the device under the condition of low false detection rate. In Figure 10, three state monitoring classification methods are applied to the training sample data of the transformer. When the false detection rate (False Positive Rate) is 16.33%, the positive positive rate of the three methods is 95.0%. 92.2%, 88.1%, 88.2%. In Figure 11, the three state monitoring classification methods are applied to the test sample data of the transformer. When the false detection rate is 17.38%, the positive detection rates of the three methods are 91.8%, 90.1%, 88.1%, and 87.5%, respectively. It is easy to see that whether the transformer sample data is training or testing, the proposed method is superior to other state monitoring classification methods in judging the state monitoring classification, which proves the effectiveness of the proposed method.

(2) Efficient efficiency based on AE-CNN-Softmax condition monitoring classification method

The feature dimension extraction and dimension reduction neural network classifier of the automatic encoder algorithm can not only effectively classify the transformer state, but also shorten the execution time of the convolutional neural network algorithm while ensuring the classification accuracy. The AE-CNN-

Softmaxalgorithm is compared with other algorithms. After the dimension reduction by the automatic encoder, the data becomes streamlined, the processing is no longer complicated, and the obtained dimensionally reduced sample data is used as the convolutional neural network classifier. The input can simplify the operation of the convolutional neural network. Therefore, the automatic encoder algorithm reduces the dimension of the data and then uses the comprehensive dimensional convolutional neural network classifier for condition monitoring and classification, which can effectively shorten the running time of the algorithm and improve the operation time. effectiveness. As shown in Figure 12, it is the running time of several state monitoring classification algorithms.

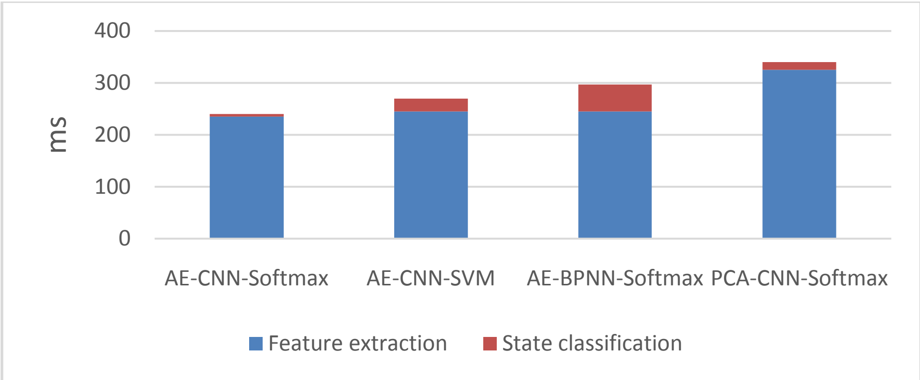

Figure 12 running time of different algorithms

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Figure captions appear below the figure, are flush left, and are in lower case letters. When referring to a figure in the body of the text, the abbreviation "Fig." is used. Figures should be numbered in the order they appear in the text.

VI. CONCLUSION

The index system of transformer condition monitoring quantity is constructed, and the feature reduction method based on self-encoding network is proposed. The experiment compares the automatic encoder dimension reduction method with the PCA dimensionality reduction method, and proves that the automatic encoder is used. The effectiveness of the method of feature dimension reduction.

A convolutional neural network condition monitoring classifier model is proposed, and the self-encoding network is used to reduce the feature vector as the input of the model.

Engineering experimental analysis shows that the AE-CNN-Softmax based transformer condition monitoring classification method is suitable for the operation of a large number of samples. Compared with BPNN, the operating state of the transformer can be obtained more accurately and effectively, not only the correct rate is high, but also the calculation speed is fast.

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