Journal of Computers Vol. 35 No. 5, October 2024, pp. 35-46
doi: 10.53106/199115992024103505003

Fault Detection Method of Oil-immersed Transformer Based on Thermal Imaging

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Received 19 September 2023; Revised 22 September 2023; Accepted 22 September 2023

Abstract. In the power system, whether the transformer can work normally and stably will directly affect the safe operation of the power grid. Monitoring the real-time operational status of transformers is crucial for the early detection, diagnosis, and resolution of potential faults. In this paper, a fault detection method of oil-immersed transformer based on thermal imaging technology is proposed. Firstly, thermal imaging images of transformer under different working conditions are obtained by infrared thermal imaging technology. Then the feature extraction and fault detection of transformer thermal image are carried out by convolutional neural network. By conducting tests and validation on actual transformers, the accuracy of fault diagnosis has reached 98.7%, thus confirming the effectiveness and precision of this method.

Keywords: fault detection, oil-immersed transformer, thermal imaging, convolutional neural networks

1 Introduction

Transformer is an important power equipment in the power system. It is responsible for the important task of long-distance transmission and conversion into low-voltage power. Due to the advantages of high reliability, low operation and maintenance costs, and good safety performance, transformer has been widely used in various occasions [1, 2]. Oil-immersed transformers with large power are generally used in power systems. Common oil-immersed transformer failures include oil leakage, excessive oil temperature, abnormal oil level, overvoltage and load, abnormal sound, and so on. Oil-immersed transformers cannot undergo regular shutdowns and maintenance. Frequent and extended shutdowns for maintenance can also impact the stable power supply in an electrical system. In the past, the staff would regularly check the operating status of the oil-immersed transformer, collect various parameters of the oil-immersed transformer in the operating state, and then use these parameters to diagnose the fault of the oil-immersed transformer. Regular inspections of oil-immersed transformers often consume significant human and material resources. Moreover, they may not promptly uncover safety risks associated with these transformers, and even some latent faults are often overlooked. Therefore, it is necessary to monitor the status of the oil-immersed transformer in real time, and repair it in time when its operating condition is not ideal.

In traditional methods, the commonly used approach is the dissolved gas analysis (DGA) of oil [3, 4]. This method allows for diagnosing the internal condition of an oil-immersed transformer while it is in operation without shutting down. The data obtained through this method is highly reliable, and the technology is well-established. The DGA method relies on the fact that the composition of dissolved gases in the oil of an oil-immersed transformer varies depending on the type of fault occurring in the transformer. The fault type of the oil-immersed transformer is determined by analyzing the composition of dissolved gases in the oil.

In recent years, with the rapid development of artificial intelligence technology and the implementation of "smart grid" policies, pattern recognition models, primarily based on artificial neural networks, have found widespread application in the field of fault diagnosis in the power system [5, 6]. Regarding transformers, traditional diagnostic methods are no longer able to meet the requirements for fast, precise, and intelligent diagnosis of transformer fault types. Chuan Zhang et al. [7] proposed a new fault diagnosis method based on the combination of discrete wavelet analysis and neural network. When the transformer fails, first use ATP/EMTP to collect the

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current, and then input the current signal into the toolbox through MATLAB/Simulink to find the best starting function. The simulation results show that the proposed algorithm is effective. In literature [8-10], a method based on fuzzy C-means clustering was proposed to identify fault types. However, this method has great limitations, because it is easily affected by initial values and fault sample size when discriminating fault types. In literature [11-13], grayscale correlation analysis, immune algorithm and data mining techniques were used to deeply and carefully classify the fault properties of transformers, and the feasibility of the proposed method was verified by the test results. Qin Hu [14] et al. used the synthetic error function in the artificial neural network toolbox to analyze and judge the types of transformer faults. The simulation results show that the fault diagnosis accuracy of this method is much higher than that of the traditional three-ratio method. M. T. Yang [15] et al. artificially solved the problem of low fault diagnosis accuracy of transformers, proposed a pattern recognition technology based on peak value, diagnostic threshold and entropy according to the feature coefficient, so as to realize the judgment of transformer fault categories. The simulation results show that the algorithm has high diagnostic accuracy. In order to solve the shortcomings of traditional DGA technology in transformer fault diagnosis, Dong-Hui Liu et al. [16] adopted SVM kernel function optimization method and combined it with embedded system and Internet of Things technology to build a set of transformer fault diagnosis system. Badar et al. [17] analyzed the temperature curve of the system in the main transformer infrared thermal imaging test of 110kV substation, and made accurate and efficient diagnosis to avoid blind power outage maintenance. Combined with the correspondence between genetic neural network and the fault point, the location of inter-turn short circuit is realized. In order to solve the problem of slight interturn short circuit in transformer coils, Ali Abdali [18] et al. proposed a new method for interturn short circuit location based on the amplitude of traveling wave reflection. A single low voltage pulse is input into the winding wire of the transformer, and the reflected traveling wave is obtained. Simulation results show that the algorithm is simple and feasible.

This article presents a fault detection method for oil-immersed transformers based on thermal imaging technology and convolutional neural networks (CNNs). This method utilizes infrared thermal distribution maps and applies CNNs for fault detection by leveraging temperature differences, enabling rapid fault localization and accurate fault type recognition. It is characterized by its immunity to electromagnetic interference and strong glare, as well as its high detection sensitivity and fast speed. To implement this method, infrared thermal images of oil-immersed transformers under different operational conditions are captured using an infrared thermal camera firstly. Given the presence of significant Gaussian and salt-and-pepper noise in the oil-immersed transformer's working environment, a combination of Gaussian filtering and median filtering algorithms is employed to remove these noise artifacts from the infrared thermal images. And then, improvements are made to the original AlexNet network model by adjusting the number of convolutional kernels, the depth of convolutional layers, and activation functions to address the issue of overfitting. Experimental results demonstrate that the proposed network model in this article achieves a 2.4% improvement in fault type recognition for oil-immersed transformers.

This paper is divided into five chapters: The first chapter is a brief introduction, primarily presenting the research motivation and the main contributions of this paper; The second chapter mainly describes our preliminary works; The third chapter introduces the fault detection method of oil-immersed transformer; The fourth chapter is experimental verification of the proposed method; The fifth chapter is conclusion and future prospect.

2 Preliminary Works

This study takes two 220kV oil-immersed three-phase transformers in the substation of Qingyang Power Supply Company of State Grid Gansu Power Company as the research object, and sets up a Hikvision DS-2TD2617T thermal imaging camera 2 meters away from the transformer to monitor the transformers in real time. As a preliminary study, this paper first selects a fixed region in the thermal imaging image as the region of interest, considering the influence of the surrounding environment and load rate on the transformer surface temperature. The oil-immersed three-phase transformer thermal imaging system is set up as shown in Fig. 1.

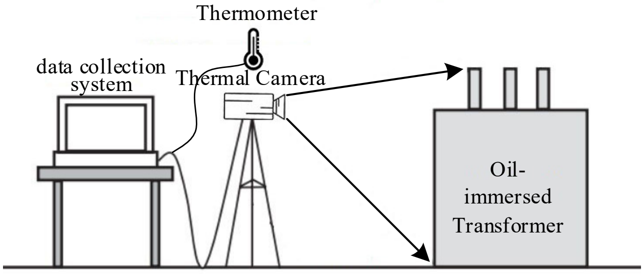


Fig. 1. Thermal imaging system of oil-immersed transformer

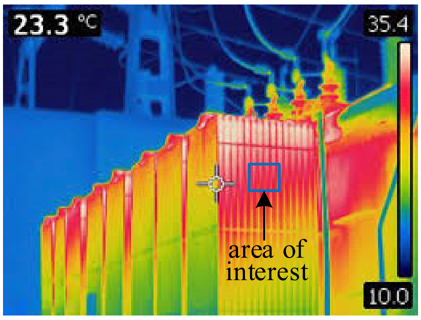
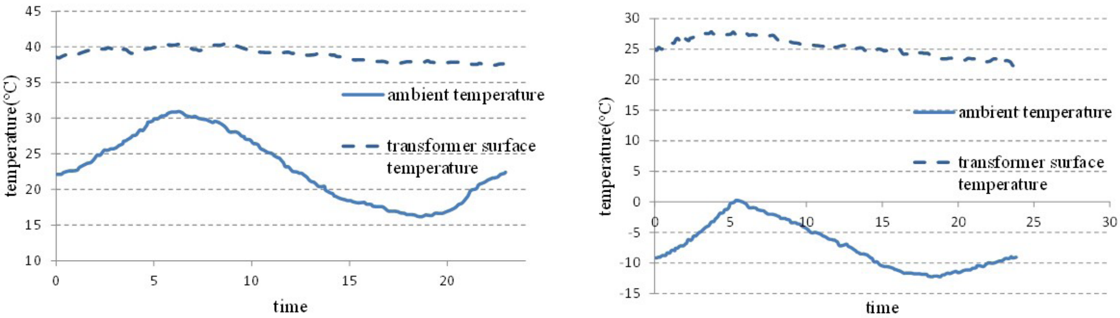


Fig. 2. Thermal imaging samples and area of interest

The oil-immersed transformer thermal imaging system consists of four parts: thermal imaging camera, thermometer, load current measuring device and data acquisition computer. We use this system to measure the ambient temperature, surface temperature and load current of the transformer from June 1st to July 31st and November 9th to January 30th. The measurement interval is 10 minutes. The thermal imaging samples collected by the system and the areas of interest are shown in Fig. 2.

2.1 Relation between Transformer Surface Temperature and Ambient Temperature

Fig. 3(a) is the ambient temperature and transformer surface temperature data measured on July 13, 2022, Fig. 3(b) is the ambient temperature and transformer surface temperature data measured on January 10, 2023. In order to exclude the influence of load rate on surface temperature, the load rate fluctuates within 10%±0.5 in these two days. It can be seen from Fig. 3(a) that the surface temperature of the transformer in one day is 40.5 degrees, and the lowest temperature is 38.1 degrees. The highest ambient temperature is 31 degrees, and the lowest temperature is 15 degrees. As can be seen from Fig. 3(a), the variation range of transformer surface temperature in summer is much smaller than that of ambient temperature. As shown in Fig. 3(b), the highest temperature of the transformer in one day is 29.8 degrees, and the lowest temperature is 25.2 degrees. The maximum ambient temperature is 3 degrees and the minimum temperature is -12 degrees. It is clear that the variation range of transformer temperature in winter is also much smaller than that of ambient temperature from Fig. 3. According to the data of the whole year, although the surface temperature of the transformer is affected by the ambient temperature, the change range is much smaller than the change range of the ambient temperature.



(a) data collected in July (b) data collected in January

Fig. 3. Relation between transformer surface temperature and ambient temperature

2.2 Relationship between Transformer Surface Temperature and Load Ratio

Fig. 4 shows the relationship between the transformer surface temperature and the load rate for 1 day measured on August 2, 2022. It can be seen from Fig. 4 that the load rate of the transformer fluctuates greatly during the time period from 8:00 to 21:00, and the change in load rate during other time periods is almost zero. At the same time, the surface temperature of the transformer changes with the load rate, and the peak positions are almost the same, and the correlation coefficient between the two reaches 0.86. It can be seen that the surface temperature of the transformer is directly positively related to the load ratio.

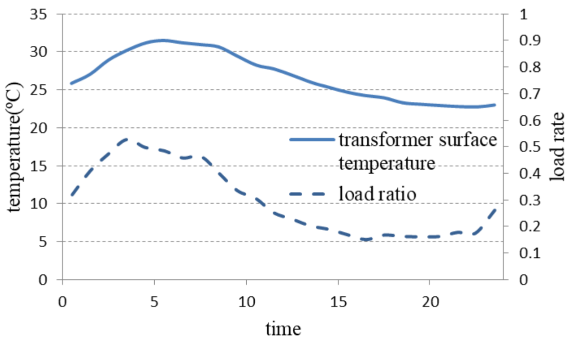


Fig. 4. Relation between transformer surface temperature and load rate

3 Oil-Immersed Transformer Fault Detection Method based on the AlexNet Network

It can be seen from the previous section that the surface temperature of the transformer is closely related to the transformer load, and has little to do with the ambient temperature. Therefore, the abnormal state of the transformer can be detected based on the surface temperature of the transformer. However, only the region of interest on the surface of the transformer can be analyzed. The fault detection of the whole transformer cannot be realized. In this section, we propose a fault detection method that takes the entire thermal image of the transformer as input to AlexNet network to identify various fault types such as abnormal cabinet heating, lack of oil in bushings, and lightning arrester heating.

3.1 AlexNet Network

The AlexNet network was first applied to image classification by AlexNet Krizhevsky et al. in 2012. It is an important milestone in the field of image classification. The AlexNet network consists of 5 convolutional layers, 3 max pooling layers, 3 local response normalization layers, and 3 fully connected layers. The structure of the AlexNet network is depicted in Fig. 5.

The AlexNet network is an improvement and advancement over the LeNet-5 network. Compared to LeNet-5, AlexNet deepens the network structure and incorporates features such as strong local area perception and weight sharing, resulting in enhanced robustness. The AlexNet network consists of a total of 25 layers. The first layer is the input layer, which has a default dimension of a 227×227×3 image. This is followed by 5 convolutional layers, and each convolutional layer is followed by an activation layer with the ReLU activation function. The first two convolutional layers are also followed by a max pooling layer and a local response normalization layer. The fifth convolutional layer is followed by a max pooling layer. The first convolutional layer has a kernel size of 11×11, a stride of 4, and 48 kernels. The max pooling layer has a pooling width of 3x3 and a sliding window with a stride of 2. The second convolutional layer has a kernel size of 5×5 and a stride of 1. The max pooling layer has the same specifications as before. The third, fourth, and fifth convolutional layers have a kernel size of 3×3, a stride of 1, and the number of kernels is 192, 192, and 128, respectively. After going through the 5 convolutional operations, the original image's abstract features are extracted, and the network has obtained information that represents classification recognition features. Following the convolutional layers are 3 fully connected layers, with the first two fully connected layers being followed by a Dropout layer each.

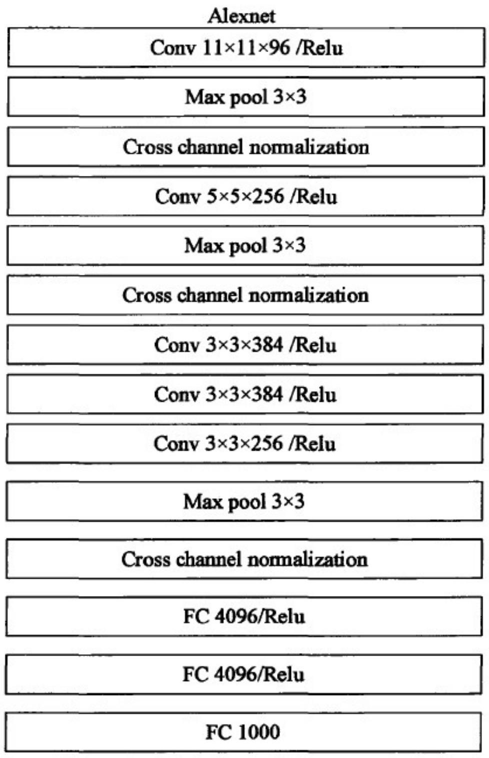


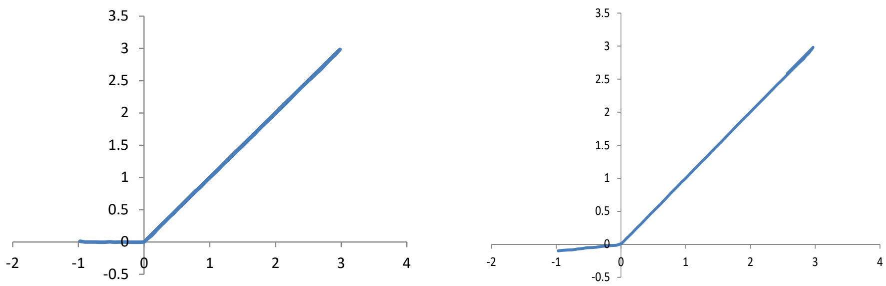
Fig. 5. AlexNet network architecture

3.2 Improvement of AlexNet Activation function

The activation function of the original AlexNet network is the ReLU function. When the input is less than 0, the ReLU function will stop abruptly even if a large gradient is propagated. Therefore, to improve this kind of problem, we changes the activation function of the original AlexNet network to the Leaky ReLU activation function. The computation formula for the Leaky ReLU activation function is shown in Equation 1.

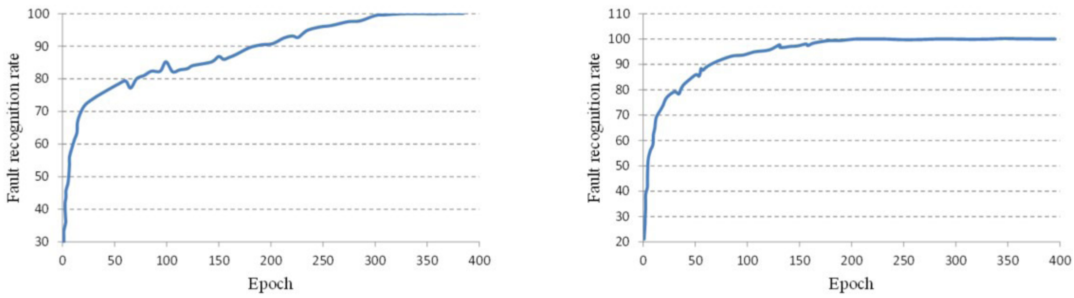
$$f(x)=\begin{cases}0.01x, & x<0\\ x, & x\geq 0\end{cases} \tag{1}$$

Compared to other types of activation functions, ReLU-type activation functions speed up neural network computations, thereby reducing training time. However, when the input is negative, the ReLU activation function renders neurons ineffective and unable to extract information from the image. In contrast, the Leaky ReLU activation function avoids this issue. When the input is negative, the Leaky ReLU activation function's non-zero derivative prevents the occurrence of silent neurons, addressing the problem of neurons not learning after entering the negative range. Therefore, compared to the ReLU activation function, the Leaky ReLU activation function effectively enhances the neural network's ability to extract features from infrared images of oil-immersed transformers. The function plots of ReLU and Leaky ReLU activation functions are shown in Fig. 6.



(a) ReLU Activation Function (b) Leaky ReLU Activation Function

Fig. 6. Activation function



(a) Chart of change in accuracy rate of ReLU (b) Chart of change in accuracy rate of Leaky ReLU

Fig. 7. Chart of change in accuracy

It can be seen from the Fig. 7 that when the activation function is the ReLU function, the network recognition accuracy change curve gradually keeps stable with the increase of training times, but the vibration amplitude is large during the training process. It indicates that the network model is not suitable for fault Identification of Oil-immersed Transformeroil-immersed. The main reason is that the neuron does not learn after the ReLU activation function enters the negative interval, so the network model does not extract the features of the infrared image in the negative interval. On the other hand, when the activation function is Leaky ReLU, the accuracy variation line chart of the network quickly stabilizes with increasing training iterations. This indicates that the improved network has addressed the issue of not extracting features from the negative range of infrared images. The network utilizing the Leaky ReLU activation function achieves a higher recognition rate for faults in oil-immersed transformers.

4 Experimental Results and Analysis

4.1 Experimental Environment and Parameter Configuration

The experiments in this study were primarily conducted on a server equipped with an Intel Core i9 3.50GHz central processing unit. Additionally, a deep learning framework based on the Python programming language was used to construct the convolutional neural network and perform comparative experiments. The training environment used for this experiment is described in Table 1.

Table 1. Experimental environment

Computer hardware	
CPU model	Intel Core i9 3.50GHz
Graphics card	GeForce2080
RAW	32G
Operating system	Win10
Python	3.9.0

This article selects a convolutional kernel size of 5 × 5. The step size is 2, the Activation function is ReLU, and the Learning rate is 0.001. The maximum number of times to learn the entire dataset is 5.

4.2 Dataset

At present, there is no public oil-immersed transformer fault thermal image data set. The data set used in this paper is provided by the State Grid Gansu Electric Power Company. It includes four types: abnormal cabinet heating, lack of oil in the bushing, lightning arrester heating and normal images. There are 183 images of abnormal cabinet heating, 274 images of lack of oil in the bushing, 192 images of lightning arrester heating and 5000 images of normal. In deep learning, the training of convolutional neural networks often requires a large number of samples, and data expansion methods are often used to expand existing data. Effective data augmentation can not only expand the number of training samples and increase the diversity of samples, but also prevent the network from overfitting and improve the performance of the network model. Therefore, in order to increase the diversity of training samples, this paper uses methods such as horizontal flipping, random picking, scale transformation and rotation to expand the existing data set. After data expansion, we obtained 500 images for training and 100 images for testing of three different types of abnormal cabinet heating, lack of oil in the bushing and lightning arrester heating.

4.3 Effect of Different Convolution Kernels Numbers on Accuracy and Training Time

In neural networks, convolutional kernels are used to automatically extract features from target images through convolutional operations. Therefore, the number of convolutional kernels corresponds to the number of features extracted by the network. For complex images with many features, more convolutional kernels should be designed; otherwise, the recognition rate will be lower due to insufficient feature extraction. For simple images with fewer features, fewer convolutional kernels should be designed; otherwise, the network may suffer from overfitting, leading to a decrease in recognition rate. Therefore, designing the optimal number of convolutional kernels is one of the key tasks in this section.

First, based on the AlexNet network model, we conducted experiments using Python to evaluate the network models with different numbers of convolutional kernels: 8, 16, 24, and 32. The accuracy and training time are presented in Table 2. According to the table, it can be observed that as the number of convolutional kernels increases, the training time also increases. The recognition accuracy of the network initially improves and then decreases with an increasing number of convolutional kernels. The highest accuracy is achieved when the number of kernels is 16. This phenomenon indicates that having only 8 convolutional kernels cannot fully extract the features from the infrared images of faults in oil-immersed transformers, resulting in a relatively lower recognition rate. On the other hand, having 24 or 32 convolutional kernels leads to overfitting issues due to excessive feature extraction by the network. Therefore, in this chapter, we ultimately selected 16 convolutional kernels. The accuracy variation curves for different numbers of convolutional kernels are shown in Fig. 8.

Table 2. Accuracy and training time of different convolutional kernels numbers

Number of convolution kernels	Training time (s)	Accuracy (%)	False alarm (%)	Missing alarm (%)
8	121	96.42	6.84	5.63
16	185	96.79	4.75	5.28
24	268	96.12	5.06	5.13
32	354	95.35	6.24	6.75

According to Fig. 8, When the number of convolutional kernels is 16, the network recognition accuracy curve fluctuates smoothly. And it remained basically unchanged after 150 training times. This phenomenon shows that this network is much better than other kernels. So, we choose a neural network model with 16 convolutional kernels.

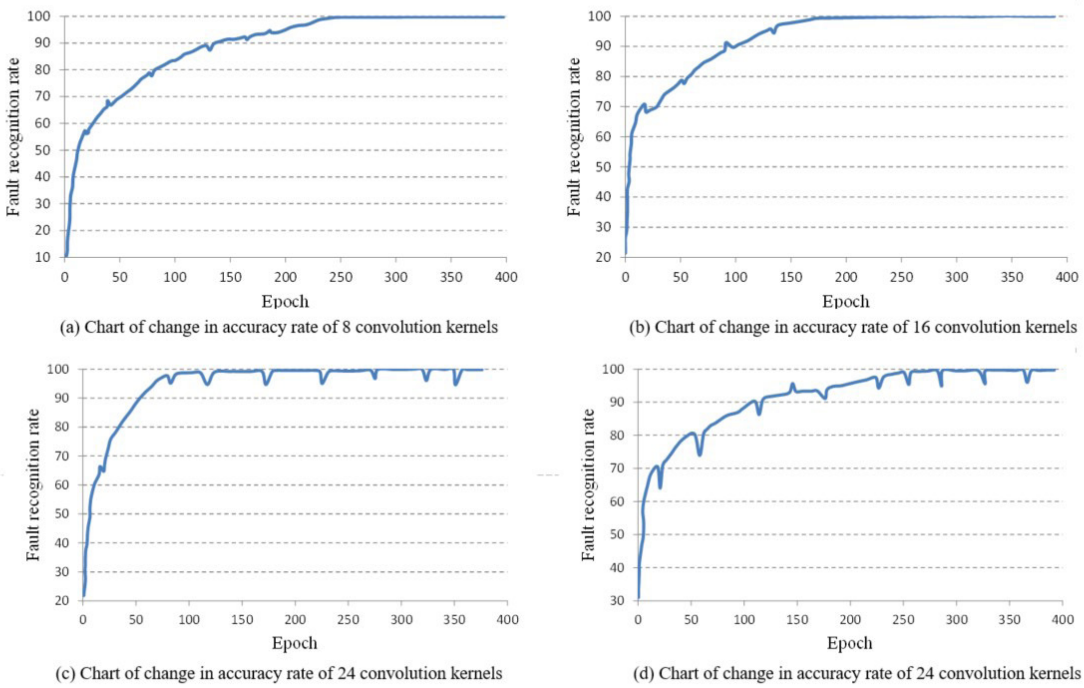


Fig. 8. Chart of change in accuracy for different number of convolutional kernels

4.4 Effect of Different Neural Network Topologies on Accuracy and Training Time

Among neural networks, the design of neural network topology has the greatest influence on the accuracy of oil-immersed transformer fault identification. In AlexNet network model, there are five convolutional layers. This paper compares the effects of different convolutional layers on network accuracy and training time, so as to determine the optimal number of convolutional layers. However, too many convolutional layers will also cause overfitting phenomenon in the network, and increase the computational amount of the network, resulting in longer training time. Therefore, designing the optimal number of convolution layers is the core work of this section.

When the number of convolutional cores in the convolutional layer is determined to be 16, Python is used to conduct simulation experiments on the network model with the number of convolutional layers being 3, 4, 5 and 6 successively. Its accuracy and training time are shown in Table 3.

Table 3. Accuracy and training time of different convolution layers

Convolution layer number	Training time (s)	Accuracy (%)	False alarm (%)	Missing alarm (%)
3	146	94.38	7.85	6.44
4	179	96.48	5.14	5.28
5	214	96.33	6.68	5.31
6	264	95.89	6.43	5.83

According to the above table, as the number of convolutional layers increases continuously, the time required for model training also increases correspondingly, but the accuracy of network model recognition increases first and then decreases. When the number of convolutional layers is 3, the number of convolutional layers is too small, so that the network cannot extract all the features in the infrared image when the oil-immersed transformer is faulty, and the network recognition rate is low. When the number of convolution layers is 4, the identification accuracy of oil-immersed transformer fault reaches 96.48%, which indicates that the network model is good for oil-immersed transformer fault type recognition. When the number of convolutional layers is 5 or 6, the network overfitting problem occurs due to the excessive number of convolutional layers, resulting in a low recognition rate. The variation curves of different convolution layers and their accuracy for oil-immersed transformer faults are shown in Fig. 9.

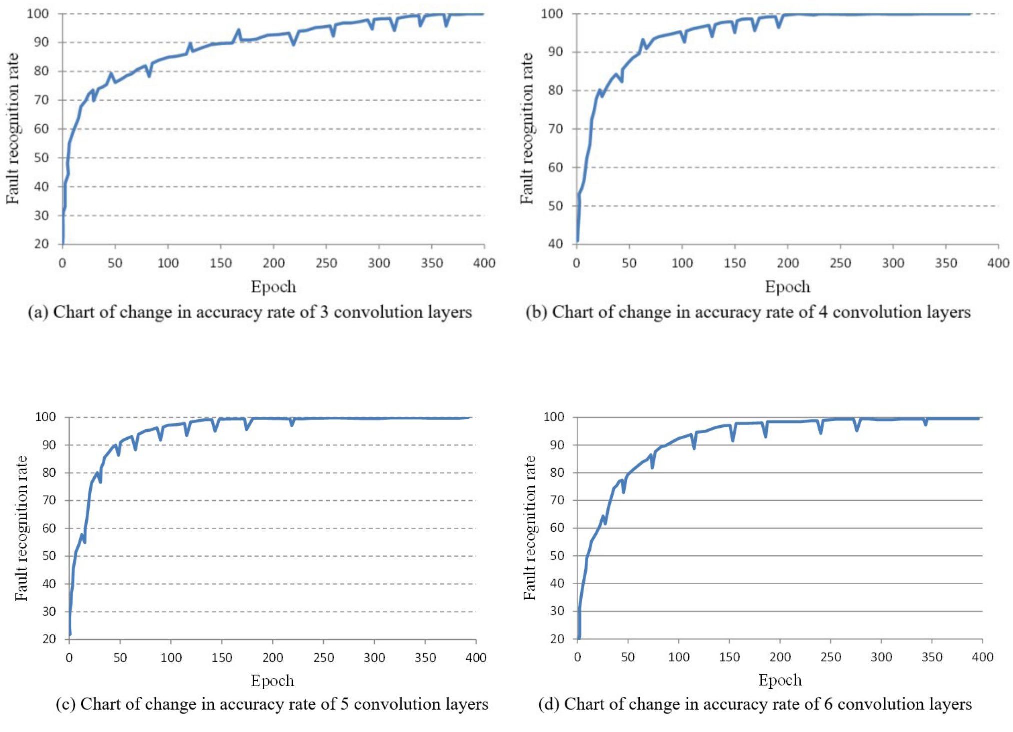


Fig. 9. Chart of change in accuracy for different convolution layers

As can be seen from Fig. 9, When the number of convolutional layers is 4, the accuracy is higher and the recognition accuracy of the neural network fluctuates relatively smoothly, and the structure of the neural network is stable. Therefore, we finally selects a neural network model with 4 convolutional layers.

4.5 Experimental Result

After the above analysis of network parameters such as activation function, number of convolution kernels, and number of convolutional layers, the improved AlexNet network structure is finally determined as shown in Fig. 10. In order to verify the fault identification effect of the improved AlexNet network, we select LeNet, AlexNet, VGG-16Net, SVM and LAT [15] and the improved AlexNet network to diagnose the fault types of oil-immersed transformers. The topology of LeNet network is simpler than that of AlexNet network, so its recognition effect is not particularly ideal. On the other hand, the topology of VGG-16Net network is too complicated, and its recognition effect is poor. Because the SVM and LAT method has a simple structure, it has the characteristics of short training time and relatively high recognition rate. Compared with the above methods, the improved AlexNet network has improved some structures, so its recognition performance has been greatly improved. The overall recognition results of the four algorithms for different fault types are shown in Table 4.

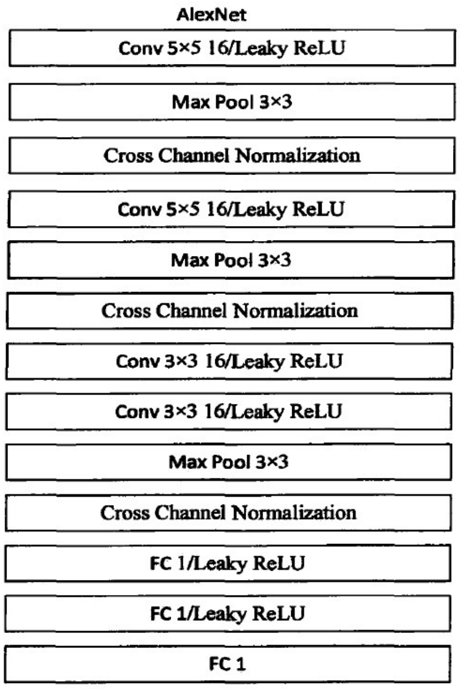
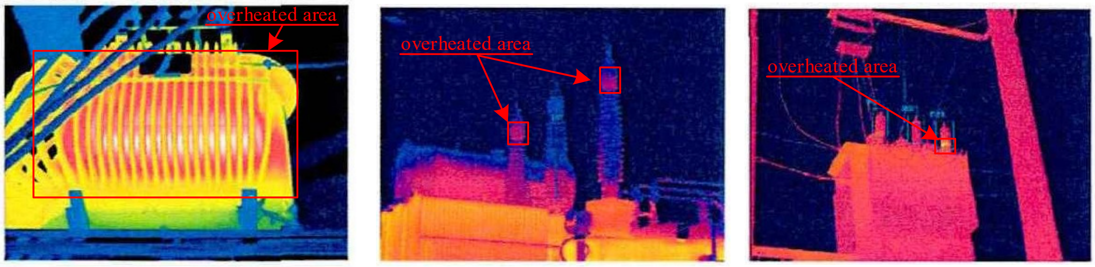


Fig. 10. Improved AlexNet network strcture

Table 4. Fault identification of oil-immersed transformer by different network models

Network model	Training time (s)	Accuracy (%)
LeNet	132	91.12
AlexNet	258	94.35
VGG-16Net	547	89.52
SVM and LAT	279	93.83
Improved AlexNet	175	96.73

As can be seen from Table 4, LeNet network has the shortest training time due to its simplest structure, but it also causes the problem of insufficient feature extraction, resulting in a low recognition rate. The VGG-16Net network has the longest training time, serious overfitting problem and the lowest recognition rate due to its complex structure. The training time and fault recognition rate of AlexNet network are satisfactory because of its reasonable structure. Because the improved AlexNet network optimizes the shortcomings of the original AlexNet network, its training time and recognition rate are greatly improved. After using the AlexNet network proposed in this paper to identify different fault types, combined with the temperature information in the infrared image, the overheated area is finally delineated. Compared to more recent methods (SVM and LAT) in recent years, it also holds a certain advantage in terms of fault recognition accuracy. The result of the identification is shown in Fig. 11.



(a)Abnormal cabinet heating (b)Transformer bushing short of oil (c)Lightning arrester heating

Fig. 11. Fault detection results of oil-immersed transformer

5 Conclusion

In this paper, Python is used to carry out experiments on the number of convolution cores and the number of convolution layers. Through comparison, it is finally determined that the network recognition rate is the highest when the number of convolution cores is 16 and the number of convolution layers is 4. An improved AlexNet convolutional neural network is proposed and tested. The test results show that the improved AlexNet network can accurately identify three fault types of oil-immersed transformer: abnormal box heating, casing oil shortage and arrester heating, and the accuracy rate is increased by 2.4% compared with AlexNet network.

Although the algorithm in this paper has a high recognition rate in the classification of infrared thermal images of oil-immersed transformers, there is no sample database on infrared thermal images of oil-immersed transformers at present, and the data set in this paper is constructed. With the use of inspection robots and the construction of intelligent substations, future researchers can improve the diversity of sample data sets by acquiring more data, so as to improve the robustness of neural network training.

In addition, there is still a lot of space for improvement in improving the topology of the AlexNet network. Since this paper only considers the impact on the recognition accuracy of the convolutional neural network from the three aspects of the number of convolutional layers, the number of convolutional kernels in the convolutional layer, and the type of activation function, we can learn from the convolutional kernel in the future. The size, size of the input image, number of iterations, and pooling methods continue to improve the accuracy of neural network recognition.

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