Research on Fault Detection Method of Infrared Thermal Imaging for Power Equipment based on Deep Learning

Cheng Li¹, *, Zixuan Yu², Mingsong Zhuo³

¹School of Information Science and Technology, Nanjing Forestry University, Nanjing, Jiangsu, 210037
²School of Electric Power Engineering, South China University of Technology, Guangzhou, Guangdong, 510006
³College of Automation & College of Artificial Intelligence, Nanjing University of Posts and Telecommunications, Nanjing, Jiangsu, 210046

*Corresponding author email: chengli@njfu.edu.cn

Abstract. With the emergence of large image sets and the rapid development of computer hardware, especially GPU, it is a challenging problem to deploy convolution neural network (CNN) model on embedded devices with limited computing resources. The overheating fault of power equipment can be identified by collected infrared thermal imaging. Due to the propagation and fading of infrared radiation in the air, the infrared temperature measurement result is lower than the actual temperature value. In this paper, an efficient convolution neural network based on embedded equipment is proposed for thermal fault detection of power equipment. The backbone network in SSD algorithm is replaced by MobileNet, and Batch Normalization is merged with the previous convolution layer, so as to reduce model parameters, improve reasoning speed and make it run on lightweight computing platform. In order to solve the problem of propagation loss of infrared radiation in the air, an infrared temperature measurement correction unit based on BP neural network is proposed. Based on the above innovation, a thermal fault detection system for power equipment is designed. Experiments and field applications show that the method has high accuracy and reasoning speed.

Keywords: Deep learning; infrared thermal imaging; lightweight; fault detection; power equipment.

1. Introduction
Substations and transmission lines in the power system are important hubs to connect power plants and users, and their safe and stable operation is very important. Once the power equipment fails, the security of the power system and the stability of power supply will be greatly affected. Power equipment is prone to failure due to climatic factors and other external environment for a long time, so it is necessary to carry out regular inspection and maintenance of power equipment to ensure the normal operation of the power supply system. According to relevant statistics, up to 90% of power system accidents are caused by power equipment failures, and more than 50% of the faulty equipment will have abnormal fever symptoms in the early stage. The principle of infrared temperature measurement is that the detector
detects and receives the infrared radiation energy emitted by the measured target, converts the received infrared radiation energy into the corresponding electrical signal, and then obtains the temperature distribution of the object surface through a special electrical signal processing system [1].

The thermal fault of power equipment is determined by the type of power equipment, heating position, heating degree and other factors, and its temperature distribution is also different. Therefore, infrared technology is very suitable for thermal fault detection of power equipment [2]. By analyzing the temperature distribution information on the surface of power equipment, we can find the potential hidden dangers and faults in power equipment, and make a quantitative judgment on the severity of the fault [3].

At present, the main form of patrol inspection in power system is manual inspection, manual on-site diagnosis or collecting information for follow-up analysis. Manual inspection has a large workload and high management cost, so technical personnel need to be trained, information collection and fault analysis need to be completed manually. However, the domestic power system is widely distributed and the environment in some areas is bad, which increases the cost and difficulty of patrol inspection, and manual inspection becomes extremely complex. If the inspection is not timely, once the power equipment fails, it will cause serious accidents. Nowadays, the fusion of convolution neural network and sensor in information technology has been widely studied and applied to power system inspection, which reduces the cost and difficulty of inspection to a certain extent. It lays a foundation for timely detection of security hidden dangers, troubleshooting and dealing with emergencies.

Convolution operation has strong feature extraction ability, has fewer parameter advantages compared with full connection layer, and has unique advantages in image data application. Convolution neural network occupies an indispensible position in the field of computer vision. However, the hardware resource limitation of embedded devices makes it difficult to deploy convolution neural networks on small devices, so the structure optimization of convolution neural networks is an important goal of this paper. Most of the calculation of convolution neural network is focused on convolution operation, so the key to reduce the complexity of the network model and the amount of calculation and parameters of the model is to design an efficient convolution structure within an acceptable range of accuracy loss. Greatly improve the speed of the network.

Since the intensity of infrared radiation emitted by the surface of the measured target will be attenuated in air propagation, the infrared temperature measurement result of the measured target is often lower than the actual temperature of the measured target. Therefore, this paper uses BP neural network to measure the infrared temperature of the measured target. The temperature measurement results are corrected.

2. Power equipment testing
Target detection is an important research field of deep learning, by obtaining target information and extracting target features for training and learning, feature classification and so on. This paper will realize the detection of power equipment on the basis of SSD, and replace the VGG-16 network in SSD with Google's efficient lightweight convolution neural network MobileNet, which is suitable for embedded and mobile terminals. Compared with SSD algorithm, it has better environmental adaptability, robustness and higher accuracy.

2.1. Power equipment detection based on embedded platform
SSD is a typical target detection algorithm based on deep learning. Compared with R-CNN series target detection algorithms, SSD cancels the resampling process of intermediate candidate boxes and pixel features to ensure the speed and accuracy of detection. SSD outputs a series of discretized candidate boxes, which generate feature maps on different layers with different aspect ratios, and go through the feed forward operation of convolution neural network.

SSD generates a series of fixed size candidate boxes, and uses small convolution Filter to predict the target category and offset in the position of the candidate box, that is, the probability that the candidate
box contains the target type. Finally, the final prediction result is obtained by the maximum suppression method [4].

However, SSD uses VGG-16 as the feature extraction network, which consumes a lot of computing resources. These network models are usually deployed on GPU, which requires very high hardware, and it is difficult to run such a huge network model on the embedded platform, which will greatly affect the detection efficiency of power equipment [5].

Figure 1 MobileNet-SSD and SSD network structure comparison

In order to make SSD suitable for embedded devices, this paper optimizes and improves SSD. We use MobileNet to replace the VGG-16 network in SSD. MobileNet uses depthwise separable convolutions to replace the conventional convolution layer. Depth separable convolution decomposes the standard convolution into depth convolution and point-by-point convolution. When the input featuremap is $m \times n \times 16$ and you want to output 32 channels, then the convolution kernel should be $16 \times 3 \times 3 \times 32$, then it can be decomposed into depth convolution: $16 \times 3 \times 3$, the 16-channel characteristic graph is obtained, and the point convolution is $16 \times 1 \times 1 \times 32$.

If the standard convolution is used, the amount of calculation is $m \times n \times 16 \times 3 \times 3 \times 32 \times m \times n \times 4608$, and the amount of calculation after deep decomposable convolution is $m \times n \times 16 \times 3 \times m \times n \times 16 \times 1 \times 32 \times m \times n \times 656$, which reduces the amount of calculation and parameters of the convolution neural network and improves the operation efficiency of the network.

The network structure of MobileNet-SSD and SSD is shown in figure 1.

2.2. Combine the BatchNormalization layer

When training deep convolution neural network, using Batch Normalization layer can accelerate the training speed and improve the convergence speed of the network. In the convolution neural network, after the Batch Normalization layer is generally placed in the convolution layer or the full connection layer, the, Batch Normalization layer normalizes the data, which can effectively solve the problems of gradient disappearance and gradient explosion, and accelerate the training fitting speed. The Batch Normalization layer plays a positive role in the training stage of the deep convolution neural network,
but in the deployment stage of the network model, there is one more layer of calculation in the model prediction, which will affect the operation speed of the model as a whole and increase the occupation space of video memory and memory. Therefore, in the deployment phase of the network model, it is necessary to merge the Batch Normalization layer into the convolution layer to improve the speed of the network model.

Suppose that the input of each layer is expressed as $X$, $W$ is the convolution weight, and $b$ is the convolution bias. The convolution operation is performed first, and the operation formula of the convolution layer is:

$$W \times Y + b$$

After the convolution operation, perform the Batch Normalization layer operation. The Batch Normalization layer performs two operations, the first is normalization, and the normalization operation formula is as follows:

$$\frac{X - \mu}{\sqrt{\sigma^2 + \varepsilon}}$$

Among them, $\mu$ is the mean, $\sigma$ is the variance, and $\varepsilon$ is a small number to prevent the denominator from being zero.

The second operation of the Batch Normalization layer is scaling:

$$\gamma Y + \beta$$

Among them, $\gamma$ is the scaling factor, $\beta$ is the bias.

After the convolutional layer and the Batch Normalization layer are merged, we get:

$$\gamma \times \frac{(W_{old} \times X + b_{old}) - \mu}{\sqrt{\sigma^2 + \varepsilon}} + \beta$$

The new convolution weights are as follows:

$$W_{new} = \frac{\gamma}{\sqrt{\sigma^2 + \varepsilon}} \times W_{old}$$

The new bias is as follows:

$$b_{new} = \frac{\gamma}{\sqrt{\sigma^2 + \varepsilon}} (b_{old} - \mu) + \beta$$

3. Infrared temperature measurement result correction

Generally, the intensity of infrared radiation emitted from the surface of an object will be attenuated in air propagation. Therefore, the infrared temperature measurement result of the measured target is often lower than the actual temperature of the measured target. The farther the distance, the greater the actual difference. So it needs to be corrected Infrared temperature measurement results of the measured target.

BP neural network algorithm is widely used in various scenarios, and when exploring the influence parameters of infrared temperature measurement, BP neural network algorithm has non-linear mapping ability compared with linear interpolation and multiple linear regression. Strong adaptability and high accuracy.
The temperature correction module will use the BP neural network to perform temperature correction on the infrared temperature measurement results. As shown in Figure 2, the input of the input layer is the infrared temperature measurement result of the measured target and the measured distance of the target, and these two types of data are input in the BP neural network, the final corrected temperature is obtained.

The hidden layer of the BP neural network designed by the temperature correction module contains $\alpha$ nodes, the input layer contains $\beta$ nodes, and the output layer contains $\gamma$ nodes. The transfer function of the neurons between the output layer and the hidden layer is a linear transfer function. Assumptions $x_i$ is the state of the neuron, $y_i$ is the output, and the relationship between the input state $x_i$ of the neuron and the output $y_i$ is linear, as shown in equation:

$$y_i = f(x_i)$$

Assuming that the $D_{i,2,...,\gamma}$ is the input of the temperature correction module BP neural network respectively, the corresponding output of the neural network:

$$E_i = D_i, \ i = 1, 2, \ldots, \gamma$$

Assuming that, $L_{i,j}^2$ and $L_{j,i}$ is the connection weight, $M_j^2, M_i$ are the bias values, then the input of the j-th node in the hidden layer:

$$F_i = L_{j1} \times E_1 + L_{j2} \times E_2 + \cdots + L_{j\gamma} \times E_\gamma + M_j$$

Therefore, the output of the j node in the hidden layer is obtained, as shown in the following formula:

$$H_j = f(x_j), \ j = 1, 2, \ldots, \alpha$$

From this, the input of the jth node in the output layer will be obtained:

$$k = \sum_{j=1}^{\alpha} L_{i,j}^2 \times H_j + M^2$$

Finally, get the output of the jth node in the output layer:

$$Y_j = f(x_j) = f(k) = k$$
4. Infrared temperature measurement result correction
In this paper, a thermal fault detection method for power equipment is designed, which combines infrared technology with deep learning, and integrates the reading of video stream, the detection of power equipment based on deep learning, the temperature correction of BP neural network and the visual fusion of data. The thermal fault detection architecture of power equipment based on embedded deep learning is shown in figure 3.

![Figure 3](image)

**Figure 3** Thermal fault detection framework for power equipment

The bottom layer is the reading of data. The infrared camera outputs the video stream in MPEG-4 format through Ethernet, and decodes the infrared camera video stream into frames and transmits it to the next layer.

The middle layer is the data processing layer, which mainly carries on the thermal fault diagnosis from the video stream of the infrared thermal imager obtained from the upper layer. A corresponding deep learning framework is built for the identification of power equipment detection algorithms in the data processing layer, and the relevant network model deployed is a trained model. This layer only carries out the detection task, not the training task of the network model. This layer is mainly responsible for real-time power equipment detection and equipment positioning; BP neural network is deployed to correct the infrared temperature measurement results; the modified temperature will judge whether the equipment has abnormal fever symptoms through a priori knowledge base.
The thermal fault diagnosis method of power equipment based on embedded deep learning is mainly divided into three tasks: detection and location of power equipment, temperature extraction of target equipment, and thermal fault diagnosis of target equipment. The class diagram is shown in Figure 4.

5. Experiment

5.1. Hardware environment
The neural network model involved in this topic will be processed in two phases: training phase and deployment phase. The hardware environment involved in the two phases is different. Due to the computing resource limitations of embedded devices, embedded devices are mainly used for deployment. The algorithm model involved in the subject does not perform training tasks. The training tasks involved in this article will be executed by a machine equipped with NVIDIA TITAN X graphics card. Jetson TX1 is the second generation of NVIDIA embedded platform development kit, with advanced Embedded vision computing system. The Jetson TX1 core is only the size of a credit card, but the Jetson TX1 GPU module has a floating-point computing power of 1 Teraflops. Obviously Jetson TX1 is an ideal embedded solution.

5.2. Demonstration of experimental results
Table 1 is the system configuration table, and Table 2 is the comparison between the actual measured temperature of some equipment and the corrected temperature. It can be seen from the table that the maximum absolute error after BP neural network correction is 1.05 °C, and the average absolute error is 0.99 °C.

| Table 1 Jetson TX1 configuration |
|----------------------------------|
| **hardware** | **Configuration** |
| GPU | NVIDIA Maxwell 256 CUDA cores |
| CPU | 64-bit A57 CPUs |
| Memory | 4 GB 64-bit LPDDR4 |
| Storage | 16 GB eMMC |
| Video Encode | 4K2K30Hz |
| Video Decode | 4K2K60Hz |
**Table 2** Comparison of partial measurement data and BP correction results (unit: °C)

| Ambient temperature | Measured temperature | Correction temperature | Absolute error |
|---------------------|----------------------|------------------------|----------------|
| 10.05               | 10.05                | 24.03                  | 0.98           |
| 15.13               | 15.13                | 26.05                  | 1.02           |
| 20.32               | 20.32                | 24.17                  | 0.93           |
| 25.60               | 25.60                | 24.03                  | 1.05           |
| 30.36               | 30.36                | 26.33                  | 0.97           |

Figure 5 is a display diagram of the thermal fault detection effect of power equipment. The detection results mark the position information of the detected power equipment in the image and the corrected temperature information. The power equipment in the green label indicates normal, and the power in the red label The device indicates an overheating fault.

![Figure 5 Test results](image)

**5.3. Performance and accuracy test**

**Table 3** Comparison of power equipment test results

| Target detection algorithm | Running speed (ms) | Accuracy(%) |
|----------------------------|--------------------|-------------|
| MobileNet-SSD              | 58                 | 86.7        |
| SSD(VGG16)                 | 597                | 92.0        |
| YOLO-tiny                  | 90                 | 80.6        |
| YOLOv3                     | 322                | 96.1        |
As shown in Table 3, we run the relevant target detection algorithm on the Jetson TX1 embedded development platform. The results show that, compared with the original SSD (VGG16), MobileNet-SSD greatly increases the operating speed within the acceptable accuracy range. An image takes only 58 ms, which is about 17 frames/s, which is of great significance for applications on embedded devices.

6. Conclusion

Aiming at the problem of fault identification of power equipment, a thermal fault detection method of power equipment based on embedded deep learning is proposed in this paper.

Firstly, the method realizes power equipment detection based on MobileNet-SSD algorithm, allows the computer to learn the characteristic information of power equipment independently and detect power equipment accurately, and uses BP neural network to correct the infrared temperature measurement results in the temperature correction module, and finally realizes the thermal fault detection of unmanned automatic power equipment.

The experimental results show that this method can detect the faults of power equipment more accurately.

At the same time, the MobileNet-SSD algorithm proposed in this paper greatly improves the reasoning speed within the range of acceptable precision. On the premise of satisfying the time performance on the lightweight computing platform, MobileNet-SSD has higher accuracy than other target detection algorithms.

Because the different equipment faults detected have different image features, and their deep features support the further reasoning of the causes of the faults, in the next stage, we will continue to use deep learning to analyze the deep causes of equipment faults.

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