Research on Transmission Equipment Defect Detection based on Edge Intelligent Analysis

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Abstract. In the transmission system, the continuous load operation and the external environment will make the equipment fault hidden danger, which will affect the stable operation of the transmission system. In this paper, an edge intelligent analysis system of transmission equipment defect image recognition is proposed. The system migrates the cloud image recognition to the edge. Feature Pyramid Network (FPN) is introduced into Single Shot MultiBox Detector (SSD) object detection algorithm based on MobileNet v1 feature extraction network to detect defects of different sizes in large-size, small-size, tower and insulator equipment. So as to realize the rapid positioning of defects and upload the results to the cloud. The results of system application show that the accuracy and recall rate of the proposed system are high. In the case of ensuring the detection accuracy, it meets the real-time requirements of detection. The system can effectively improve the automation level of transmission equipment operation and maintenance. While improving the operation and maintenance efficiency of transmission lines, the safe operation of the transmission system is ensured.

1. Introduction

The fault of transmission equipment will directly affect the normal operation of the transmission channel and cause serious safety and economic losses[1,2]. It is of great significance to identify and diagnose the operation status of transmission equipment for the security, reliability and economy of power grid operation [3].

With the rapid development of artificial intelligence technology, the application of image recognition in transmission operation and maintenance has become a hot research direction in recent years [4]. Compared with the traditional manual detection, it can greatly improve the work efficiency and detection accuracy [5]. It can also improve the automation level of transmission equipment operation and maintenance. At the same time, its application can reduce the work pressure of operation and maintenance personnel, so as to improve the security and stability of power grid operation [6].

At present, some researches have been carried out in power grid inspection image processing technology. In reference [7], a multi-angle adaptive recognition algorithm for insulator self-exposed defects under complex background based on aerial photography is proposed to realize automatic detection of defective insulators. In reference [8], a method based on image processing and pattern recognition technology to identify insulator, shock hammer and transmission tower is proposed. In reference [9], the structure and parameter optimization of deep convolution neural network were designed to realize automatic identification of foreign matters through Tensorboard module of...
Tensorflow in transmission lines. In reference [10], a Faster Region-Convolutional Neural Network (Faster R-CNN) based on VGG16 is proposed to realize the identification and detection of transmission line fault images.

It can be seen from the above analysis that the current equipment defect detection of power transmission system is to upload the image taken by the field detection equipment to the cloud. Then the image recognition method deployed in the cloud is used to detect and diagnose the defect of equipment [11]. This kind of method can reduce the labor intensity of staff, but cloud processing can not timely and effectively deal with equipment defect. At the same time, there are high requirements for data computing performance and data transmission performance in the cloud [12]. Therefore, this paper proposes a set of edge intelligent analysis system of transmission equipment defect image recognition, which migrates the cloud equipment defect recognition to the edge end. The system can quickly locate and identify the equipment defects on the edge intelligent analysis equipment and upload them to the cloud. It can effectively improve the operation and maintenance efficiency of the transmission line and ensure the safe operation of the transmission system.

2. Overall Framework of Intelligent Edge Analysis System for Image Recognition of Transmission Equipment

The structure of the transmission equipment defect detection system proposed in this paper is shown in Figure 1. The terminal of transmission equipment condition monitoring is equipped with edge intelligent analysis equipment. The terminal will collect the image data through real-time or specific period image capture and transmit the data to the edge intelligent analysis device. The edge intelligent analysis device detects the defects of the transmitted image. Then, the image data of detected defects is uploaded to the defect sample database of cloud server. When the sample database is updated, the updated defect sample data is used for training. And the defect detection model is adjusted and optimized to complete the model updating through training. Finally, the optimized model is updated to the edge intelligent analysis device to realize the iterative optimization of the model.

![Figure 1. Framework of fault edge intelligent analysis system for transmission equipment.](image)

3. Algorithm of intelligent Edge Analysis System for Image Recognition of Power Transmission Equipment

The edge intelligent analysis system of power transmission equipment image recognition uses SSD object detection algorithm based on MobileNet v1 feature detection network. Considering the small distribution proportion of some targets in the image, FPN algorithm is added for training.

For the identification of transmission equipment defects at the edge intelligent analysis system, the algorithm performance should ensure both speed and accuracy. Therefore, this paper uses SSD target detection [13] algorithm to make the detection process into a single deep neural network, which is
convenient for training and optimization and improves the detection speed at the same time.

3.1. SSD Object Detection Algorithm
SSD object detection algorithm uses a small filter to predict the categories and bias of bounding boxes in different size feature map layers, which can obtain better results in smaller input images. At the same time, the overall end-to-end design achieves better trade-off between detection speed and detection accuracy. The basic architecture is shown in Figure 2.

Figure 2. SSD algorithm overall framework.

The objective function of SSD algorithm is divided into two parts: the confidence loss of the corresponding default box and object category and the corresponding location loss. Where N is the number of prior boxes whose IOU = 0.5 and matches the ground truth. If N = 0, the loss is set to 0. The α is used to adjust the ratio between confidence loss and location loss. The default value of α is 1, see formula (1).

\[
L(x, c, l, g) = \frac{1}{N} \left( L_{\text{conf}} (x, c) + \alpha L_{\text{loc}} (x, l, g) \right)
\]

where \( L_{\text{conf}} (x, c) \) denotes confidence loss, which is softmax loss on multi-class confidence c. The formula is shown in (2). \( L_{\text{loc}} (x, l, g) \) is smooth L1 loss of location regression, and the formula is shown in (3).

\[
L_{\text{conf}} (x, c) = - \sum_{i} \sum_{p} x_{ij}^p \log(C_{ij}^p) - \sum_{i} \sum_{p} x_{ij}^\text{neg} \log(C_{ij}^\text{neg})
\]

where i is the search box number. j is the real box number. p is the category number. \( x_{ij}^p \) indicates that the i-th prior box matches the j-th ground truth box. Taking I indicates that the i-th prior box matches the j-th ground truth. \( c_{ij}^p \) represents the prediction probability of category P corresponding to the i-th search box.

\[
L_{\text{loc}} (x, l, g) = \sum_{i} \sum_{j} \sum_{m} \sum_{n} x_{ij}^m \text{smooth}_{ij} \left( l_{ij}^m - g_{ij}^m \right)
\]

where \((cx, cy)\) is the center of d of the default box after register to offsets. \((w, h)\) is the width and height of the default box.

3.2. Feature Extraction Algorithm of MobileNet V1
MobileNet V1 focuses on the lightweight Convolutional Neural Network (CNN) network in the mobile terminal or embedded devices [14]. Its core idea is depthwise separate revolution. Depthwise separate revolution consists of two layers: depth convolution and point by point convolution. We use depth convolution to convolute each input channel with a single convolution kernel to get the depth of input channels. Then use point by point convolution, that is, a simple 1x1 convolution is applied to realize the linear combination of the output in depth convolution.

Suppose that \(D_F\) is the width and height of the input feature graph. M is the number of input channels. N is the number of output channels and \(D_K\) is the spatial dimension of convolution kernel.

The computational complexity of depth convolution and point by point convolution is \(D_F D_K M D_F D_F + M N D_F D_F\). Through the process of integrating the volume into filtering and combination, the reduced amount of calculation is obtained in formula (4).

\[
\frac{D_K D_K M D_F D_F + M N D_F D_F}{D_K D_K M N D_F D_F} = \frac{1}{N} + \frac{1}{D_K^2}
\]

All layers of MobileNet V1 use batchnorm and Rectified Linear Unit (ReLU) nonlinear activation
functions. Except for the last layer, there is no nonlinear activation function directly sent to softmax layer for classification.

3.3. FPN Network

The overall structure of FPN network is divided into bottom-up and top-down and side connection processes [15], as shown in Figure 3.

![Figure 3. Overall structure of FPN.](image)

The bottom-up part is a common feature extraction network. In top-down and side connection, the top-down is the process of feature map enlargement, which is usually realized by up sampling.

The cleverness of FPN is that sampling from high-level features can make use of both the top-level semantic features and the low-level high-resolution information. Upsampling can be implemented by interpolation. In order to combine the high-level semantic features with the accurate positioning ability of the bottom layer, a lateral connection similar to the residual structure is used. The lateral connection fuses the features of the upper layer after up sampling and the features with the same resolution of the current layer by adding. At the same time, 1x1 convolution is used to keep the channel number of all levels consistent.

4. Intelligent Edge Analysis System for Image Recognition of Power Transmission Equipment

Jetson Nano, an artificial intelligence computer, provides a complete desktop Linux environment with accelerated graphics. It supports NVIDIA CUDA Toolkit, cuDNN and TensorRT libraries. The SDK also includes native installation of popular open source machine learning frameworks, such as Tensorflow, PyTorch, Caffe, Keras and MXNet. It also supports the framework of computer vision and robot development, such as OpenCV and ROS. The structure diagram is shown in Figure 4.

![Figure 4. Structure diagram of a Jetson Nano.](image)
The structure of Jetson Nano is illustrated as follows: (1) represents CPU + GPU; (2) represents CSI camera; (3) represents DC power interface; (4) represents display port interface; (5) represents HDMI HD interface; (6) represents USB 3.0 interface; (7) represents Gigabit Ethernet interface; (8) represents micro USB interface; (9) represents WIFI connector.

Jetson Nano provides real-time computer vision and reasoning for a variety of complex Deep Neural Network (DNN) models. These functions support Internet of Things devices with intelligent edge analysis and advanced AI systems. Even transfer learning can use the ML framework to retrain the network locally on the Jetson Nano.

5. Application Analysis of Intelligent Edge Analysis System for Image Recognition of Power Transmission Equipment

5.1. Test Samples and Training Parameters
The edge recognition system of transmission equipment image recognition is applied to the transmission system. The defects of four kinds of transmission equipment are identified and analyzed, including large-size equipment, small-size equipment, tower and insulator. The defects of large-size equipment in the sample set include the hammer corrosion, the hammer falling off and the clamp corrosion. The defect of small-size equipment is the lack of pin. The defect of tower equipment is the bird’s nest on the tower. The defects of insulator equipment include the falling of glass insulator and the pollution flashover of porcelain insulator. The division ratio of training set and validation set in the sample set is 0.85:0.15, and the detailed quantity division is shown in Table 1.

| Number of Pictures | Training Set | Validation Set | Test Set | Total |
|--------------------|--------------|----------------|---------|-------|
| Large-size Equipment/Piece | 1174 | 208 | 245 | 1627 |
| Small-size Equipment/Piece | 3260 | 576 | 678 | 4514 |
| Tower Equipment/Sheet | 921 | 163 | 192 | 1276 |
| Insulator Equipment/Piece | 3462 | 611 | 719 | 4792 |

The total number of defect samples and the corresponding tag number distribution of the four types of equipment are shown in Figure 5.

![Figure 5. Quantity distribution of equipment defect labels.](image)

The pre-training model used in the algorithm in this paper is based on the ImageNet public dataset. The main training parameters are shown in Table 2.
Table 2. Training parameters.

| Training Parameters | Value |
|---------------------|-------|
| Batch_Size          | 24    |
| Optimizer           | rms_prop |
| Learning_rate       | 0.001 |
| Momentum            | 0.9   |
| Batch_norm          | True  |

5.2. Analysis of Test Results

Four kinds of equipment defects are diagnosed and analyzed after training. The recognition effect of the edge intelligent analysis system for power transmission equipment image recognition is evaluated by statistical analysis of the average accuracy (map), accuracy (precision), recall rate (recall) and single image detection speed (speed). The results of the assessment are shown in Table 3 and Table 4.

Table 3. Model evaluation form.

|                          | Large-size Equipment | Small-size Equipment | Tower Equipment | Insulator Equipment |
|--------------------------|----------------------|----------------------|-----------------|--------------------|
| Map                      | 0.532                | 0.51                 | 0.549           | 0.527              |
| Precision                | 0.88                 | 0.826                | 0.851           | 0.861              |
| Recall                   | 0.831                | 0.819                | 0.833           | 0.879              |
| Speed (s/frame)          | 0.061                | 0.065                | 0.062           | 0.059              |

Table 4. Recognition results.

| Category | Large-size Equipment | Small-size Equipment |
|----------|----------------------|----------------------|
| Original Picture | ![Image] | ![Image] |
| Detection Result | ![Image] | ![Image] |

Category | Tower Equipment | Insulator Equipment |
|----------|-----------------|---------------------|
| Original Picture | ![Image] | ![Image] |
| Detection Result | ![Image] | ![Image] |

According to the above table, the average accuracy of the four types of equipment identification is more than 0.51. The average accuracy of tower identification is the highest, which is 0.549. The lowest is 0.51 for small-size equipment. The accuracy of large-size equipment identification is the highest, reaching 0.88. The recognition rate of small-size equipment lowest, which is 0.826. The accuracy rate of the other two types of equipment also exceeded the index of 0.85. The recall rate of insulator identification is highest, which is 0.879. The lowest is 0.819 for small-size equipment. And the recall rate of other two types of equipment is above 0.83. The detection speed of small-size equipment is 0.065 second/frame. The detection speed of tower is slowest, which is 0.062 second/frame. The detection speed of all devices is about 0.06 second/frame.

On the whole, the intelligent edge analysis system of transmission equipment image recognition
proposed in this paper has high accuracy and recall rate for defect identification and detection of large-size equipment, small-size equipment, tower and insulator. Under the condition of ensuring the accuracy of defect detection, the detection speed is improved, which has high practical application value.

5.3. Cloud Intelligence Analysis
The defect image detected at the edge will be uploaded to the cloud. The cloud enriches the defect sample library by calibrating the uploaded defect images. Then, the updated defect sample library is used for model training to realize model optimization and iterative optimization. An example of a cloud interface is shown in Figure 6.

Figure 6. Cloud interface example.

6. Conclusion
In this paper, a set of transmission equipment defect image recognition edge intelligent analysis system is proposed from the perspective of transmission equipment defect image recognition and edge intelligent analysis. The conclusions are as follows:

1) The image recognition algorithm based on deep learning is transferred to the edge. Compared with the defect detection of equipment image in the cloud, it not only reduces the transmission amount of image data, but also improves the operation and maintenance efficiency of the system.

2) Through the system application verification, the accuracy rate and recall rate of large-size equipment, small-size equipment, tower and insulator identification are high. The detection speed of the system is also fast, which can effectively meet the defect identification requirements of transmission equipment inspection. It is convenient to detect and distinguish the equipment defects in the inspection site. It can also effectively improve the efficiency of judging the operation status of transmission equipment in the operation site, so it has significant application value.

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