Lightweight Neural Network for Component Recognition and Fault Detection of Large-Scale Transmission Line

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Abstract. Recognition and fault detection of transmission line components is a basic problem that puzzles the development of smart grid. However, due to the limitation of current datasets, it is difficult to carry out large-scale model training and mobile reasoning based on artificial intelligence technology. Although the current standard datasets for the classification of components in transmission line scenarios contain many different types of objects, they are all smaller datasets based on a certain category. This paper constructs and annotates 10,226 standard image Power Database which contain 6 component categories (including 3 fault component categories). In addition, aiming at the problem that the general target detection algorithm infers too slowly or can not run in the real-time inspection process of transmission line mobile terminal equipment, a model MSFF-KCD (Multi-scale feature fusion in key component detection) is presented, which combines the multi-scale feature fusion method with the detection of transmission line key components. Experiments on real-time component identification and fault detection by deploying the model to mobile devices show that the proposed method establishes a new performance bound and this method suitable for mobile terminal detection of key components of transmission lines. We also compared the models of recognition and detection for large and small targets on Power Database, which provided enlightenment for the identification and fault detection of power components.

1. Introduction

The recognition and fault detection of transmission line components is an important part of circuit inspection. It is of great significance for the prevention of major accidents in power system to accurately recognize the faults of transmission line components and eliminate the hidden dangers in time [1, 2].

The traditional inspection method of transmission line, which is based on the observation of artificial or auxiliary helicopter and integrated use of human sensory fusion back-end data analysis, has low efficiency, high work intensity and blind area. At present, with the help of unmanned aerial vehicle (UAV) for data collection, combined with the back-end data analysis system to complete the inspection of transmission lines, although the inspection efficiency has been improved and the labor cost has been reduced, there are problems that the data analysis and front-end interaction are not timely, and the fault can not respond quickly. With the rapid development of deep learning technology,
artificial intelligence is continuously combined with the power industry, and impressive results have been achieved in the intelligent inspection task [3-5]. Although the precision of intelligent detection and recognition technology based on deep learning is high, due to the limitation of reasoning speed and power data set of mobile end, the data analysis is still completed on the server or cloud end, which becomes the bottleneck restricting the development of power patrol inspection [2]. The combination of mobile devices and artificial intelligence technology for transmission line fault and real-time detection at mobile terminals has become the development trend of circuit inspection [6], as shown in Figure 1.

At present, the main difficulties in the application of the combination of mobile devices and artificial intelligence technology to the transmission line fault detection task can be summarized as follows: first, the current deep learning algorithms are based on the low-resolution data set, and the model itself pays more attention to the multi texture and large-size targets, while the image of transmission line inspection has high-resolution, small size and low texture. It is required that the model pay more attention to the detection of small moving objects, which increases the difficulty of model detection, such as shock hammer, insulator and other components; secondly, most of the deep learning models are trained and optimized based on the standard data set, and their image size, resolution, lighting conditions and categories are relatively balanced, which can play the advantages of deep learning. However, in the field of transmission line inspection, there is no standardized transmission line data set at present. The existing data sets have large data differences, information confusion, and obvious imbalance, which makes the algorithm happen when the detection accuracy of one class is excellent and the detection accuracy of another class is low [2]; finally, the training and reasoning of deep learning model consumes computing resources very much, while the transmission line data set consumes computing resources very much. The computing power and volume of line fault mobile devices such as UAV chips are limited, so how to combine the front and back systems and deploy the deep learning algorithm in the mobile devices for real-time transmission line detection is an urgent problem.

To solve this problem, this paper constructs and labels 6 component categories (including 3 fault component categories) with 10226 standard image database. In addition, a model MSFF-KCD (multi scale feature fusion in key component detection) is proposed, which combines multi-scale feature fusion method with key component detection, to solve the problem that the general target detection algorithm is too slow or unable to run in the mobile terminal reasoning. The experiment of real-time recognition and fault detection of components by deploying the model to mobile devices shows that this method establishes a new performance boundary, which is suitable for the detection of key components of transmission lines at mobile terminals, which provides an indication for the recognition and fault detection of power components.
2. Dataset construction of Power Database for large-scale transmission lines
Since there is no standard data set for deep learning model training for transmission line component identification and fault detection at this stage, we collected and marked 10226 Power Database image datasets with LabelImg tool, as shown in Figure 2. The source of the original data set is the photos of UAV inspection transmission line provided by an inspection unit under State Grid Corporation. The shooting of the inspection data is in accordance with DL/T 1482-2015 technical guidelines for UAV inspection of overhead transmission lines, which is a real and effective data. After cleaning and screening, this paper focuses on the research of insulator, shockproof hammer, suspension clamp, insulator explosion, shockproof hammer failure, bird’s nest.

Figure 2. Illustration of Power Database images
Recognizing and detecting the power database is a challenging task. First of all, the picture background of Power Database transmission line components dataset is complex and diverse, and the number of samples in each category is relatively balanced, covering a variety of real field environments such as substations, transmission towers, field plains, mountains and rivers, forests, towns, etc.; secondly, because of the shooting distance, shooting angle and other reasons, the proportion of components in the picture area is different, which increases the difficulty of model training; At last, there are many small components stacked on the transmission line, which block each other, which brings a challenge to the fault detection of small components.

3. MSFF-KCD model architecture
By analyzing the characteristics of power database, we can find that the key components (insulator, shockproof hammer, suspension clamp, insulator explosion, shockproof hammer failure, bird’s nest) included in the image account for a small proportion of the area of the whole image, and most of the components account for less than 5%. This is different from the traditional target detection methods, which pay more attention to the small size and low ripple rational targets for the transmission line component identification and fault detection. Based on the above considerations, we propose MSFF-KCD model which pays more attention to small target detection [7-10]. The model architecture is shown in Figure 3, which includes the deep separable convolution module (DPNets), multi-scale redundant feature fusion module, detection and classifier module and non maximum suppression module.
3.1. Deep separable convolution module

In order to make the model run faster on the embedded arm device, this algorithm combines the characteristics of key components and uses the deep separable convolution idea [8-9,11] to design a lightweight feature extraction DPNets module to save computing power and speed up reasoning. In the depth separable convolution module, the channel and region are considered at the same time in the standard convolution operation, and the region is considered first, then the convolution operation of the channel is considered. The separation of the channel and region is realized. Finally, the standard convolution is integrated into depth convolution and point by point convolution. Depth convolution is responsible for filtering and point by point convolution is responsible for converting the channel. Compared with the standard convolution, the parameters of depth separable convolution are greatly reduced.

This module uses the depth separable convolution to design a 14 layers feature extraction network DPNets with an input size of 640×640×3 to extract the depth features of key components. The specific parameters are shown in Table 1, where Conv represents the ordinary convolution operation and DepthSepConv represents the depth separable convolution operation.

| Layer Name | FilterSize/Step | Input Size | Feature Icon | Receptive Field |
|------------|-----------------|------------|--------------|-----------------|
| Conv_0     | 3×3/s2/32       | 640×640×3  | -            | 3               |
| DepthSepConv_1 | 3×3/s1/64 | 320×320×32 | CV0          | 7               |
| DepthSepConv_2 | 3×3/s2/128    | 320×320×64 | DP1          | 11              |
| DepthSepConv_3 | 3×3/s1/128    | 160×160×128 | DP2          | 19              |
| DepthSepConv_4 | 3×3/s2/256    | 160×160×128 | DP3          | 27              |
| DepthSepConv_5 | 3×3/s1/256    | 80×80×256  | DP4          | 43              |
| DepthSepConv_6 | 3×3/s2/512    | 80×80×256  | DP5          | 59              |
| DepthSepConv_7 | 3×3/s1/512    | 40×40×512  | DP6          | 91              |
| DepthSepConv_8 | 3×3/s1/512    | 40×40×512  | DP7          | 123             |
| DepthSepConv_9 | 3×3/s1/512    | 40×40×512  | DP8          | 155             |
| DepthSepConv_10 | 3×3/s1/512   | 40×40×512  | DP9          | 187             |
| DepthSepConv_11 | 3×3/s1/512   | 40×40×512  | DP10         | 219             |
| DepthSepConv_12 | 3×3/s2/512   | 40×40×512  | DP11         | 251             |
| DepthSepConv_13 | 3×3/s1/256   | 20×20×256  | DP12         | 315             |

3.2. Multi scale redundant feature fusion module

In order not to reduce the accuracy performance of the model, according to the size of the receptive field of each feature layer of DPNets, this paper introduces the multi-scale feature fusion method [10] combined with the elimination of redundancy to improve the feature learning ability. We combine the low resolution and high semantic feature map with the high resolution and low semantic feature map to increase the ability of low-level feature extraction. As shown in Figure 4, the basic method of the multi-scale feature fusion module is to fuse the low-resolution features with the high-resolution...
features through deconvolution operation, and perform different convolution operations on each fused feature map to obtain multiple feature maps under multiple scales for prediction at the same time.

In this process, although the advantages of deconvolution operation are obvious, with the increase of feature map, the corresponding redundant feature information will increase, at the same time, it will reduce the detection speed, and then affect the overall detection effect. Therefore, in this paper, the redundant feature elimination processing is carried out among the feature graphs. We select the feature graphs FF1 and ff4 without deconvolution operation, and use the 3×3 small convolution kernel to filter the redundant information of the feature graphs FF0, FF2, FF3 and FF5 after deconvolution operation to achieve multi-scale feature fusion learning. The steps are as follows:

Step 1: do 1×1 convolution operation on DP4, DP10 and DP12 to reduce the channel of the feature map, and obtain three feature maps of FF4, FF1 and DP4';
Step 2: deconvolution FF4 and FF1-FF4' to obtain FF4' and DP10'. The size of the feature map of FF1 and FF4' is the same, and that of DP10' and DP4' is the same;
Step 3: DP4'-DP10', FF1-FF4' and FF4 three feature maps are respectively 3×3 samconvoluted to obtain three feature maps of FF0, FF2 and FF5;
Step 4: make convolution kernels of 3×3, steps of 2, and depth of 256 for FF5 feature graphs from step 3, and get FF3;
Step 5: 6 feature maps of FF0, FF1, FF2, FF3, FF4 and FF5 from step 1 to step 4 are used for prediction at the same time.

4. Experiment and evaluation

In this paper, average precision (AP), recall and mean average precision (mAP) are used to evaluate our model. The threshold is set to 0.5.

The off-line end of the experimental environment is Ubuntu 16.04 system, the CPU is Intel (R) Core (R) i7 6800k 3.4 GHz × 12, the memory is 16g, the GPU is NVIDIA (R) GTX (R) 1080 and the deep learning framework is tensorflow 1.13. The mobile terminal relies on NVIDIA Jetson AGX Xavier, an embedded arm device with edge computing capability.

According to the ratio of 7:2:1, the dataset is divided into three parts: train set, verification set and test set. After the initial training and optimization of the offline model, the reasoning test of the mobile model is carried out. As shown in Figure 5, the offline end completes continuous dynamic training through our patrol inspection support system. The system provides a visual module package for efficient off-line training, and interacts in Chinese style, including six modules: dynamic creation of data set, management of data set samples, training model, verification model, detection test and visualization of detection results. Then the offline trained model is off the shelf and loaded on the UAV equipped with embedded arm device for testing. After the UAV test is completed, the newly collected data is injected into the off-line end to continue the model training, so as to achieve closed-loop training and reasoning.
Figure 5. Illustration of power patrol inspection support system. The system mainly consists of 6 modules from figure (a) to figure (f): dataset creation, dataset management, training, verification, detection and visual display of detection results.

The method MSFF-KCD proposed in this paper is compared with other five baseline methods (SSD_VGG16 [7], SDD_Inception_v2 [12], SDD_ResNet50 [13], SDD_MobileNet_v1 [14], SDD_MobileNet_v2 [15]) on Power Database, as shown in Table 2. Experiments show that the mAP of this method is 0.83 and recall is 0.75. Far higher than the other five classic methods. The reasoning speed of MSFF-KCD model in mobile terminal is 15FPS, which shows excellent reasoning performance. We also compare the average accuracy of each target of power database, as shown in Table 3. The experiment shows that compared with the other five methods, the method in this paper achieves the best results in six kinds of targets: insulator, shockproof hammer, suspension clamp, insulator explosion, shockproof hammer failure, bird’s nest. This shows that the MSFF-KCD model can deal with this kind of power data well for the high resolution, small size, low texture and other characteristics of the image of transmission line inspection.

Table 2. Comparison of experimental results on Power Database.

| Method               | mAP@0.5 | Recall@0.5 | Inference Speed |
|----------------------|---------|------------|-----------------|
| SSD_VGG16[7]         | 0.74    | 0.63       | 14FPS           |
| SDD_Inception_v2[12] | 0.74    | 0.63       | 18FPS           |
| SDD_ResNet50[13]     | 0.75    | 0.69       | 11FPS           |
| SDD_MobileNet_v1[14] | 0.71    | 0.62       | 24FPS           |
| SDD_MobileNet_v2[15] | 0.74    | 0.66       | 24FPS           |
| MSFF-KCD             | 0.83    | 0.75       | 15FPS           |

Table 3. Comparison of the AP of each object in different models on Power Database.

| Method               | insulator | shockproof hammer | suspension clamp | insulator explosion | shockproof hammer failure | bird’s nest |
|----------------------|-----------|-------------------|------------------|---------------------|---------------------------|-------------|
| SSD_VGG16[7]         | 0.82      | 0.61              | 0.79             | 0.53                | 0.83                      | 0.85        |
| SDD_Inception_v2[12] | 0.81      | 0.62              | 0.80             | 0.53                | 0.82                      | 0.84        |
| SDD_ResNet50[13]     | 0.83      | 0.64              | 0.80             | 0.52                | 0.85                      | 0.87        |
| SDD_MobileNet_v1[14] | 0.81      | 0.60              | 0.76             | 0.49                | 0.81                      | 0.82        |
| SDD_MobileNet_v2[15] | 0.83      | 0.63              | 0.78             | 0.53                | 0.84                      | 0.86        |
| MSFF-KCD             | 0.90      | 0.90              | 0.80             | 0.58                | 0.91                      | 0.94        |

5. Conclusion

In view of the lack of large-scale standard dataset for deep learning model training in component detection of transmission lines, this paper constructs and labels 6 component categories (including 3
fault component categories) with 10226 standard image databases. In addition, aiming at the problem that the general target detection algorithm is too slow or unable to run in the process of real-time inspection of transmission line mobile devices, a model MSFF-KCD which combines multi-scale redundant feature fusion method with the detection of key components of transmission line is proposed. In order to make the off-line training model more convenient, we developed a power inspection support system. The real-time identification and fault detection experiments of components in mobile devices show that this method establishes a new performance boundary, which is suitable for the detection of key components of transmission lines in mobile devices.

In the future, we will focus on the recognition and detection of all kinds of components and equipment whether the fault, what kind of fault and the fine detection of fault degree, and develop an intelligent system for fault detection and identification of transmission line equipment based on deep learning.

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