Deep Learning Method for Buffer Layer Defect Detection in High Voltage Cable

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Abstract: A deep learning method based on the convolution neural network is proposed to replace the manual inspection for the buffer layer defect detection in high voltage cable. One hundred seventy-seven high-resolution images of defects are collected. The VGG16 network is adopted. The results indicated that the VGG16 achieves the F1 score to 0.68 on the test set, proving to be an efficient way to detect the buffer layer defects.

1. Introduction
High voltage XLPE cable, with its good electrical performance, is widely used in power systems [1-2]. The cable buffer layer is located between the insulation shield and the metal sheath, which plays a vital role in the stability of cables’ electrical and insulation performance [3]. In China, body failure caused by cable buffer layer ablation frequently is occurring in recent years [4-5].

Previous studies have shown that common detection techniques for existing power equipment, such as partial discharge detection, cannot effectively detect buffer layer defects [6-8]. The X-ray digital imaging technology [9] can effectively and intuitively carry out defect inspection on buffer Layer.

In recent years, the deep learning technique represented by the convolutional neural network (CNN) [10] is continuously surpassing the previous image recognition techniques in the classification task. It is gradually applied in many professions.

In this paper, on-site X-ray image data set collected from a cable tunnel is established. Then, the buffer layer defects are identified by using the technology based on CNN, thus providing an effective way to liberate the workforce.

2. CNN model
The convolution neural network comprises the input layer, convolution, the activation layer, the sampling, the fully connected layer, and the output layer. The input layer is the X-ray image after image processing. Ordinarily, a high-resolution image cannot be directly used in the input layer because of the limited calculation condition. We can use the sliding window or size reduction method to fit the input layer's image size. The convolutional layer is mainly used to extract image features. In particular, the upper input is checked by convolution for convolution operation. The convolution kernel reduces the connection between different layers to avoid excessive fitting and many parameters. The activation layer is mainly used to enhance the data's nonlinear characteristics and improve the model's expression ability. The downsampling layer is mainly used to extract the data's main features.
and reduce its size. One-dimensional data are generated from the two-dimensional convolutional layer or the last layer's downsampling layer and then processed by the traditional one-dimensional neural network in the fully connected layer. The output layer is the final output result of the model, mainly generating corresponding category probability according to different input data.

VGG network [11] is a convolution neural network model developed by the Computer Vision Group of Oxford University and Google DeepMind researchers in 2014. VGG network structure is simple and has good generalization performance. The typical network VGG16 is shown in Figure 1.

![Figure 1. VGG16 network](image)

3. The defect detection method flow chart
The flowchart of our defect detection method is shown in Figure 2 and demonstrated as follows:

Step 1. Image acquisition: Use a CCD or flat panel detector to obtain an X-ray digital grayscale image.

Step 2. Image preprocessing: Use contrast adjustment, edge sharpening, window width and window level adjustment for grayscale images to form an image suitable for human eyes to judge defects. Then, the image is classified and labelled with or without flaws, and the image with defects can be processed with image enhancement.

Step 3. Model training: The CNN model is used for training, and the hyperparameters of the model are set to obtain the parameters of the trained model.

Step 4. Model evaluation: Use the F1 score to evaluate model performance.

Step 5. Model saving: Save the trained model.

Step 6. Model testing: Test the new data set using the trained model.
Figure 2. Flowchart of our defect detection method

4. Example
We collected 177 original X-ray images in this example from a cable tunnel. For the original high-resolution image, the sliding window method is used to cut the image into local images, and the local images with defects are labelled at pixel-level. In this example, the original image resolution is 2176×1972, and the local image resolution is 224×224. The sliding window's stride is 112, and each local image marked with defect pixels is rotated by 90, 180 and 270 degrees to enhance the generalization capability. Finally, we get 12833 local images, in which 8656 local defect images are used for training, and the rest of the local images are used for testing. The VGG16 network is adopted. The deep learning library TensorFlow is used for model training.

The cross-entropy loss function is used as follows:

\[ \text{Loss} = -y \log y' - (1 - y) \log (1 - y') \]  

where, \( y \) denotes the positive and negative label; \( y' \) denotes the output probability.

The evaluation indexes of the model are as follows:

\[ \text{Precision} = \frac{TP}{TP + FP}, \text{Recall} = \frac{TP}{TP + FN} \]  

\[ F1 = \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \]

where, TP denotes the true positive predictions; FP means false positive predictions; FN denotes the false-negative predictions.

The model training process is as follows:
For the VGG16, the initial learning rates are set as 0.001, and the SGD updater is used. The weight decay to use for regularizing the model is set to $10^{-5}$ to prevent overfitting. The VGG16 is trained for 1000 epochs, and the batch size is set as 15.

As can be seen from Figure 3, the Loss and mIoU converge after about 200 epochs on both the training and test sets except the training Loss, which decreases gradually. However, there are some unstable jump points in the training process. The F1 score finally achieves 0.68 on the test set. Meanwhile, Figure 4 shows some recognition results on the test set, which indicates that the VGG16 is an efficient way to detect the buffer layer defects.

5. Conclusion
This study adopts a deep learning method for high voltage XLPE cable buffer layer defect detection. The location of the buffer layer defect can be automatically acquired by the CNN method. The on-site
cable X-ray images are used to verify the VGG16, which is finally proved to be useful. In the future, higher performance models and more data should be used to improve the defect detection effectiveness.

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