Image Defect Detection and Segmentation Algorithm of Solar Cell Based on Convolutional Neural Network

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Abstract—**The use of infrared or electroluminescence(EL) images of solar cell modules for defect detection is a very important method in non-destructive testing. Traditionally, this work is done by skilled technicians, which is time-consuming and susceptible to subjective factors. The surface defect detection method of solar cells based on machine learning has become one of the main research directions because of its high efficiency and convenience. For this reason, this paper proposes an improved fusion model based on VGGNet and U-Net++, which is used for defect detection and segmentation of EL images of solar cells. In the defect detection stage, the input image is processed pertinently, and by modifying the convolutional layer and the fully connected layer of the network, while improving the performance of the algorithm, it accelerates the convergence and avoids the phenomenon of over-fitting. In the defect segmentation stage, the defect location is marked based on the public data set, which is used for the training of each segmentation model, and the effect of different segmentation networks is compared to select a reasonable model. The experimental results show that the defect detection accuracy of the improved VGG16 network on the elpv-dataset is 95.2%, and the U-Net++ defect segmentation model has an average MIoU value of 0.955, which is better than other existing methods.**

Keywords-component; defect detection; convolutional neural network; deep learning; U-Net; electroluminescence image

I. INTRODUCTION

With the intensification of the world energy crisis, solar power has become one of the important directions of the energy transition. The core component of photovoltaic solar energy is the solar cell module, which can directly convert solar radiation energy into electrical energy and store it in storage equipment. The effectiveness of solar panels is strictly limited by the magazines and defects in photovoltaic modules. In order to adopt appropriate methods to suppress the formation of serious defects, it is of great significance to understand the physical properties of defects. With the development of digital image processing technology, defect detection technology based on machine vision has gradually replaced manual detection methods, and has been practiced in industrial production[1]–[3].

A brief introduction to the defect detection method of solar cell images based on machine vision is as follows. First, from the imaging methods of visible light, thermal infrared , photoluminescence and EL imaging of solar cell modules, the solar cell modules are imaged. And then the pixel distribution information and characteristics in the image are used to detect defects. The detection methods can be roughly divided into: methods based on gradient features[4], methods based on matrix decomposition[5] and methods based on machine learning[6]. The method based on machine learning has become a current research hotspot because of its efficiency and convenience[7], [8].

In 2014, Wang X B[9] established a DBN based on sample characteristics, and fine-tuned the network parameters through the BP algorithm, but the detection accuracy was low. In 2018, Deitsch S[10] proposed a method to detect defects in EL images, and compared the training and prediction effects of SVM and CNN. The detection accuracy of defect images reached 82.44% and 88.42%. In 2019, Daniel S[11] used vesselness algorithm to automatically process solar cell images, and used Fourier filtering to enhance the image quality. The effect was better. In 2020, Qian X L[12] combined short-term and long-term deep features to detect solar cell microcracks, but it cannot detect defects on the initial image.

In view of the low accuracy of traditional defect detection algorithms and the separation of detection and segmentation tasks, this paper combines the improved VGGNet[13] model and U-Net++[14] model for the first time, using a combination of classification mechanism and end-to-end pixel detection mechanism, which can effectively complete defect image detection and defect recognition. The main contributions of this article are as follows: 1) A method for detecting defects in solar cell images based on deep learning is proposed, which uses VGG16 as a feature extraction network to detect whether the image contains defects, and redesigns the convolutional layer and the fully connected layer to improve the detection accuracy; 2) We built a defect segmentation model based on the U-Net++ framework and compared it with the segmentation effect of FCN[15] and U-Net[16]; 3) It is the first time to integrate VGGNet and U-Net++ for solar cell image defect detection tasks. On the elpv-dataset, the effectiveness of the method is verified.

II. METHOD

The solar cell image defect detection and segmentation algorithm based on convolutional neural network can be divided into defect detection and defect segmentation. The algorithm flow chart is shown as in Figure 1. Step 1: After the original data is preprocessed by filtering and normalization methods, the training set and the test set are divided. Then they are input into the improved VGG16 model to complete the defect image detection. Step 2: The defect image is generated by a custom label generator to generate segmentation image labels, which are used for model training.

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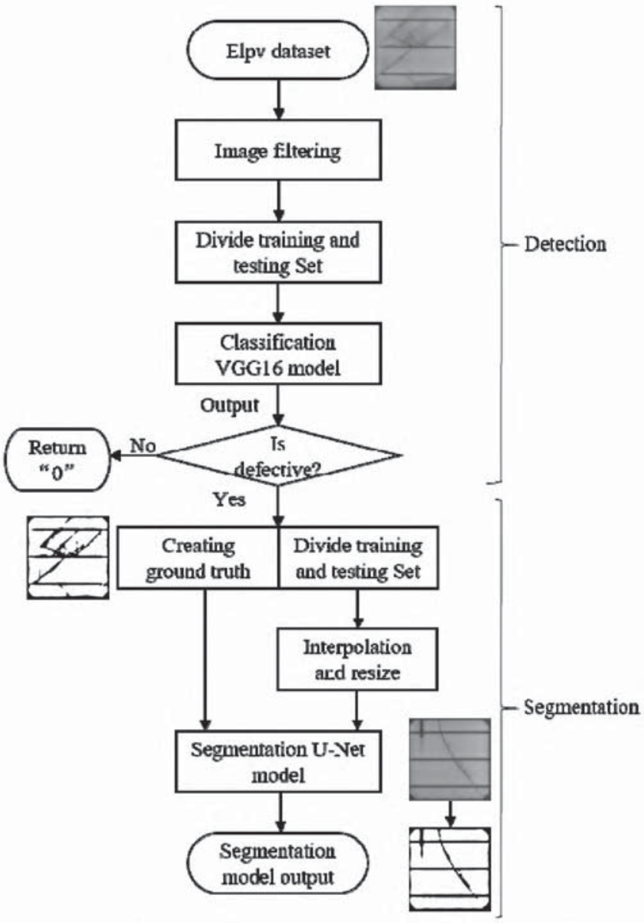

Figure 1. Defect detection and segmentation algorithm flow chart.

A. Our VGG16 model

VGG16 is composed of 13 convolutional layers, 5 pooling layers and 3 fully connected layers. Our improved VGG16 network structure is shown in Figure 2. The VGG network has 3 input image channels, we copy the original single-channel grayscale image to a three-channel RGB image. In order to meet the requirements of input size, the size of each layer of the convolutional layer is adjusted, and a normalization layer is introduced into the convolutional layer to speed up the network convergence. After the output of the last pooling layer, the image features are connected to a fully connected layer containing 41472 neurons. In order to prevent the model from overfitting, a dropout layer is added to the latter two fully connected layers, with the probability.

B. Segmentation model

We build FCN, U-Net and U-Net++ segmentation networks based on the Pytorch framework, and then use the defect dataset for training. The FCN network can accept the input of images of any size, and use deconvolution to restore the last layer to the original size of the input image. The first half of U-Net is used for feature extraction, and the second half is for up-sampling. It splices features together in the channel dimension to form thicker features. U-Net++ is a multi-scale dense skip connection convolutional network, and its main structure is to shrink and expand the backbone. It is first an encoder sub-network or a backbone network, and then a decoder sub-network. Each sub-network decodes the down-sampling results of each layer of the backbone network. Finally, all the decoding results are combined with the main extension backbone of each layer. Each Conv model consists of four convolutions, each of which has a 3×3 kernel.

C. Label generation for defect images

The original data does not provide images with defect marks. This article creates a custom image label generator. It mainly consists of three steps: 1) Histogram equalization processing: to increase the global contrast of the image; 2) Unsharp filter: to sharpen and enhance the image of the correct shape; 3) Ostu threshold segmentation: to realize automatic threshold segmentation of grayscale images. The filtered and normalized image is input to the image label generator to generate a binary image with defect marks.

III. Experiments

A. Dataset

The elpv-dataset provided by Buerhop-Lutz, C[17] is used in the experiment. The image data comes from 44 different solar cell modules, and contains a total of 2624 300×300 pixel 8-bit grayscale image samples. In order to reduce the difference caused by unbalanced data distribution, pictures with a probability of 0% of defects are regarded as positive samples without defects, and pictures with probability of 33.33%, 66.67% and 100% are regarded as negative samples with defects.

Due to the influence of environmental factors in the image acquisition stage, the original data will inevitably have problems such as black spots, poor contrast, and dirt. Before the image is input to the network model, preprocessing operations are required. Based on the filtering principle, the median filter method is selected to process the original image, which effectively eliminates the influence of image noise and protects the sharp edges of the image. In the filtering process, the convolution kernel parameter is set to 7×7. After the image is filtered, the average and normalization operations are introduced to accelerate the training speed.

We use 80% of the original data set as the training set and 20% as the test set, and input them into the classification model. For the problem of unbalanced sample distribution, the method of data enhancement is adopted. There are a total of 1116 defective images in the data set. After the defective image labels are generated, 80% of them are used as the training set and 20% as the test set, which are input into the FCN, U-Net and U-Net++ networks to complete the training and testing process.

B. Experimental conditions and parameter settings

This experiment was carried out on the Pytorch platform built on the Ubuntu 16.04 (64 bit) operating system, using NVIDIA TITAN V to implement GPU accelerated training. The training process took 6.2 hours. Both defect image detection and image segmentation can be considered as two-classification tasks, so the two-class cross-entropy loss function is used in the model training process. This experiment uses the Adam algorithm of adaptive moment estimation, which combines the advantages of AdaGrad and RMSProp algorithms.

C. *Defect detection results*

The main indicators for evaluating the performance of a classification model are accuracy rate (ACC) and F1-Score, etc., where ACC represents the proportion of all the correct results of the model to the total number of samples. F1-Score integrates the effects of accuracy and recall. F1-Score ranges from 0 to 1, with 1 representing the best model and 0 representing the worst output performance of the model.

After a large number of parameter adjustments, the loss function changes steadily after 200 generations of training, and the model converges. The confusion matrix of the classification results is shown in Table 1. Comparing the detection method in this paper with other methods, our method have a high detection accuracy rate of 95.2%. The average recall rate of the model is 0.954, and the F1-score is 0.944. The results are shown in Table 2. Based on the above indicators, the detection effect of our method is better.

TABLE I. CONFUSION MATRIX OF CLASSIFICATION RESULTS

Confusion Matrix		**True value/ *Pixel***	
		Positive	***Negative***
Predicted Value/ *Pixel*	***Positive***	1065	75
	Negative	51	1433

TABLE II. COMPARISON OF DETECTION ACCURACY OF DIFFERENT

Model	*ACC/%*
CNN[10]	88.4
LeNet-5[18]	90.0
GoogleNet[19]	88.7
VGG16[20]	93.9
Our method	**95.2**

D. *Defect segmentation results*

We use accuracy (PA) and mean intersection over union (MIoU) to measure the performance of image segmentation. PA is defined as the ratio of the number of pixels with the correct prediction category to the total number of pixels. The MIoU is the average between the IoU of the segmented objects over all the images of the test dataset and IoU is the ratio between the area of overlap and the area of union between the ground truth and the predicted areas.

We train the U-Net++ and U-Net networks under the same parameter settings, and compare the segmentation effects of U-Net, U-Net++ and FCN. As shown in Table 3, the U-Net++ network has the highest MIoU value of 0.955, which is higher than U-Net(0.929) and FCN(0.892). Figure 3 shows the segmentation effect of monocrystalline and polycrystalline solar cell modules on U-Net and U-Net++. After careful comparison, it can be found that the defect segmentation effect of the model in this paper is the best, and more attention can be paid to the details of the defect.

TABLE III. EVALUATION INDEX OF SEGMENTATION EFFECT

Model	*PA/%*	*MIoU*
FCN[15]	91.9	0.892
U-Net[21]	94.4	0.929
Our method	**96.8**	**0.955**

E. *Experiment analysis*

Compared with other methods, this paper adopts the more complex network structure of VGG16 and U-Net, and expands the input size of the VGG16 convolutional layer to 300×300, which retains more image information. By setting the dropout layer, the robustness of the model is improved. Thus, the accuracy of the model is greatly improved. Through complex parameter adjustment, the convergence performance of the model is better.

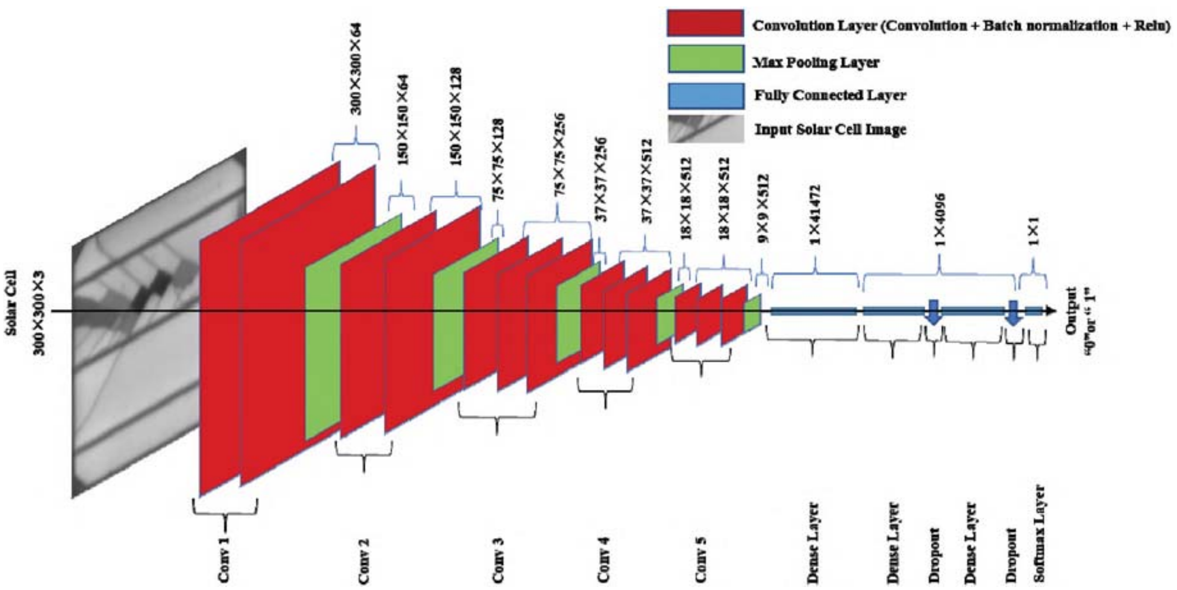

Figure 2. Improved VGG16 network structure.

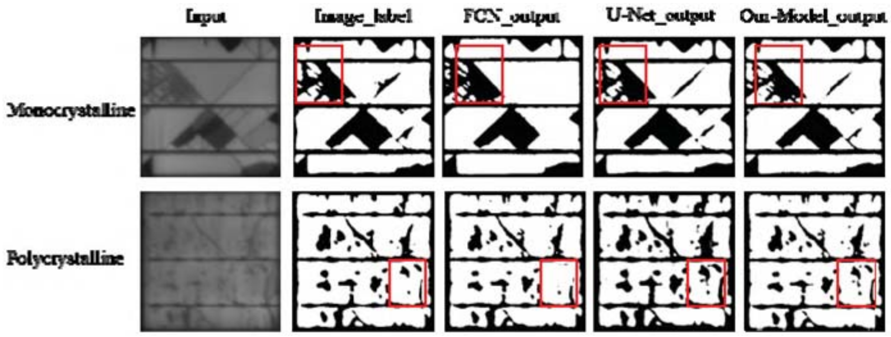

Figure 3. Model segmentation results.

IV. CONCLUSIONS AND FUTURE WORK

This paper proposes a solar cell image defect detection and segmentation algorithm based on the combination of VGG16 network and U-Net++ network. We train the two models on the open source dataset and the labeled dataset. Experiments show that the defect detection accuracy rate based on the improved VGG16 network reaches an average of 95.2%, and the defect segmentation network U-Net++ network MIoU value reaches 0.955. The models performs well in all aspects, which provides a new way for defect image detection and segmentation. However, due to the limitations of the researcher's ability and experimental conditions, there are still some problems. The follow-up work will focus on defect location and further explore model optimization issues.

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