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Defect Localization and Classification of Photovoltaic EL Based on Deep Learning

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Abstract

To locate and classification the defects of photovoltaic cells accurately, neural network detection algorithm based on Faster RCNN was proposed. We use improved K-means ++ clustering algorithm to select the clustering center instead of manually selecting the size of anchor. At the same time, we select different basic backbone network, the balance between speed and accuracy has been achieved. The use of ROI Align in the final pooling operation eliminates the double quantization and makes the model more accurate in locating small objects. Experimental results show that the accuracy of the improved detection algorithm for some defects on photovoltaic cells can reach 98%, and the average detection time for a single image is 0.55s. Compared with the basic Faster RCNN, the performance is improved to a certain extent and can be used in engineering.

Keywords

Photovoltaic cell; Deep learning; Bilinear upsampling; Faster RCNN.

1. INTRODUCTION

With the development of society, the problems of environment and energy have been paid more and more attention. Solar energy as a new type of energy, low carbon, environmental protection, inexhaustible advantages have been widely praised by the people [1]. Photovoltaic cell is carrier of energy conversion, the production of cells is increasing. The quality of the cells affects the conversion efficiency of solar energy to a great extent. Moreover, some defects such as crack and debris may occur in the production process of the battery, leading to local heating, even fire in serious cases. The common defect types are shown in Figure 1. Production quality greatly affects the prospects of enterprises and even the whole industry. Therefore, how to control the quality of the cell production process is one of the key issues for the development of the photovoltaic industry.

In Photovoltaic cell manufacturing, it is necessary for defect detection Traditional detection is manually reviewed, which is subjective, cannot achieve high the accuracy of detection and wastes a lot of human resources. To apply automatic detection to engineering, many classical detection algorithms have been proposed by scholars. For example, traditional feature extraction method [2-3], it is necessary to set the defect type in advance and extract the corresponding features for defect classification. Sai used the background reconstruction method [4-5] to subtract the original image from the diffuse image and separated the defect area by multi-threshold segmentation. Chiou [6] used infrared imaging technology and chromatic aberration to distinguish the crack area from the common grain area, to achieve the purpose of defect detection.

The development of deep learning also promotes the research of photovoltaic defect detection. Depends on the powerful computing power and huge amounts of data, Deep learning uses multiple convolution kernels to extract features and uses back propagation to update the

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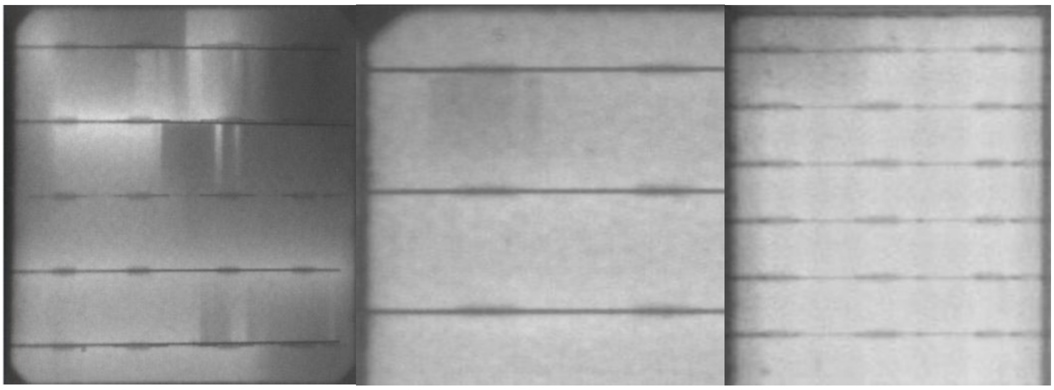
parameters of the convolution kernels. After training the network with many images, you can use the trained model to detect the defects in the generation process of cell [7]. However, the development of deep learning is late, and there are few defect detection algorithms of photovoltaic cells based on deep learning. To improve the detection efficiency of cell defect, we use the improved Faster RCNN network model to locate and detect cell defect in this paper. Finally, we use the data set to conduct experiments to verify the effectiveness of the algorithm.



a) yinlie b) duanshan c) xuhan

Figure 1. Cell defect type

2. RELATED WORK

Object detection is one of the popular directions in computer vision. The main detection frameworks are divided into two categories: 1.one-stage method, YOLO network model [8]. YOLO is the representative works of this method, plays a pivotal role in both academic and engineering fields due to its advantage in detection speed.2. Two-stage method. The two-stage detection algorithm is divided into two parts: "finding the object region" and "what is the object". This method has many steps, so the two-stage detection algorithm is inferior to the single stage detection algorithm in the detection speed. But two-stage detection has higher detection accuracy, it is still widely used in the industrial field. Faster RCNN algorithm [9], as one of the classic algorithms in the two-stage algorithm, is mainly divided into three parts:1. Feature extraction network, 2. RPN network,3. FAST classification network.

2.1. Feature Extraction Network

Since the 2012, some classic network models have been proposed in ImageNet competition. For example, the winner of the 2012 competition: AlexNet [10]. AlexNet add Relu activation function, Dropout for reducing the risk of overfitting, local corresponding normalization network LRN and other techniques to the convolutional neural network at the first time and become the top 1 in the competition. In the 2014 competition, competitors proposed the GoogLeNet network [11] and the VGGNet[12]. In recent years, the depth of the convolutional neural networks has become deeper and deeper. GoogLeNet and VGGNet proposed to use multiple small convolution kernels instead of large convolution kernels to extract deeper features, multiple small convolution kernels can increase the nonlinear combination and reduce the amount of computation. Include champion in 2015: residual network ResNet [13], which uses residual blocks to make skip connection, which can effectively reduce overfitting while the number of network layers is increasing. These network models can extract image features well and become the feature extraction trunk network of subsequent network models.

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2.2. RPN Network

Region Proposal Network(RPN) is one of the most important innovations of Faster RCNN network, which greatly improves the training and testing speed. In the previous RCNN series, the selective search[14] method was generally used to extract the region of interest(ROI).Selective search uses traditional image features such as color and texture. Selective search extract two thousand regions of interest from images by exhaustive method or sliding window and send them to the classification network. These two thousand regions of interest cover all possible locations which contain the object. But this approach has an obvious drawback: high computational complexity. Sliding window method will produce many redundant regions, and the method cannot consider all features in the image at the same time, so the location of ROI is not accurate. The proposal of the RPN network solved this problem.

RPN network propose an important concept of anchor. Anchors represent candidate boxes for detecting object. After the feature extraction network, we can get the feature map of the image. RPN network uses the sliding window method to generate anchor with different scale and aspect ratio at each point on the feature map. Assuming that the size of the feature map is W×H. With three different scales and ratios, we can obtain W×H×9 anchor point frames. The coordinates of these anchor boxes are based on the original image, and anchor sizes are manually specified by a priori information. Then these anchor boxes are input into the two network layers to get the classification score and coordinate position of each anchor, where the coordinate position is the relative offset of ground truth. The classification score is used to judge whether the anchor box belongs to the foreground, and the positive and negative samples are selected according to a certain proportion for training. The network structure of RPN is shown in Figure 2.

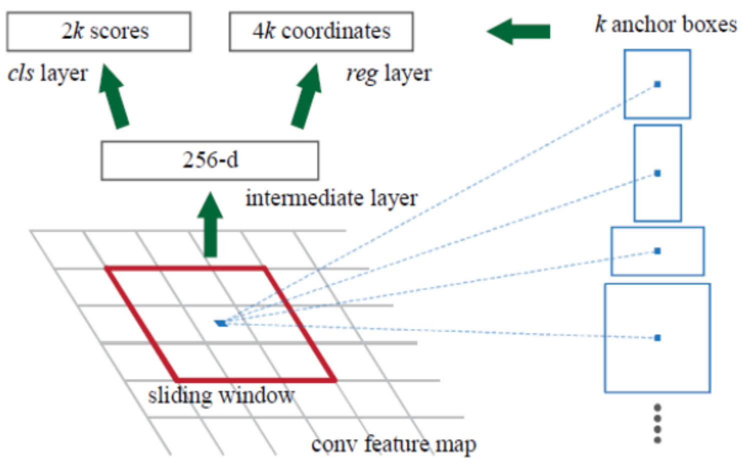

Figure 2. RPN network structure

3. IMPROVED FASTER RCNN

In order to better apply Faster RCNN to the photovoltaic industry, we propose an improved Faster RCNN algorithm. The improved algorithm is mainly considered from three perspectives. 1. The choice of anchor is generally selected by manual experience. We use the improved unsupervised clustering k-means++ algorithm to cluster the target prior frame to obtain a more suitable anchor size; 2. we add Feature Pyramid Network (FPN) [15] to the feature extraction network to obtain feature maps of multiple scales, which is conducive to the detection of small targets; 3. we use bilinear interpolation to offset the quantization operation in the pooling layer to obtain more accurate position coordinates.

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3.1. k-mean++ Clustering

The k-means algorithm is one of the classic unsupervised clustering algorithms. It uses the distance metric as the criterion to divide the samples into k clusters, which makes the samples in the clusters to be as close as possible, and the samples between the clusters to be as separate as possible. K-means algorithm is fast and simple, but it has obvious shortcomings: first, we need to set the value of k, and difference value of k will obviously affect the effect of clustering; second k cluster centers need to be initialized randomly, and different cluster centers will cause different clustering effect. In order to solve this problem, we use the modified k-means++ algorithm [16] for anchor clustering. k-means++ algorithm led to the distance between each cluster center to be as far as possible. we realize k-means++ algorithm as follow.

1) Randomly select a sample from input data as the first cluster center c1.

2) For each sample x in the data set, calculate the distance D(x) between it and the nearest cluster center (referring to the selected cluster center), and select a new cluster center ci according to the probability.

3) Repeat process 2) until k cluster centers are found.

3.2. FPN Network

In the application field of deep learning, small target defect detection has always been one of the bottlenecks that limit detection performance. In the process of feature extraction, the network needs to convolve the image multiple times. According to the characteristics of convolution, as the number of channels of the feature map increases, the size of the feature map will gradually decrease. Therefore, in this process, small targets in the picture are more likely to be ignored. In order to better detect small targets, we add the feature pyramid network to the feature extraction network.

The low-level feature semantic information is relatively small, but the target location is accurate; the high-level feature semantic information is richer, but the target location is relatively rough. In order to comprehensively consider the two aspects of information, we use multi-scale prediction to fuse the high-level features and the low-level features, and then send them to the subsequent network for classification and prediction.

3.3. ROI Align

There are two steps in the framework of the faster RCNN algorithm. first, many anchor frames are obtained after RPN network. Second, we perform classification and regression after ROI Pooling. In this process, there are two quantization operations. For the first quantization, we round the coordinates because when the region of interest is mapped to the feature map, the coordinates of the original image and the coordinates of the feature map are not completely aligned. For the second quantization ROI pooling will resize the feature map of the anchor box into a specified size, in order to fix the feature map to a uniform size and make it easier to send the feature map to the final fully connected layer for classification prediction. Although only a small part of the pixels are omitted, when the feature map is mapped back to the original image, the error will be magnified, which will affect the detection and classification effects of the network.

$$F_p \approx \frac{(x_1-x)(y_1-y)}{(x_1-x_0)(y_1-y_0)}F(Q_1)+\frac{(x-x_0)(y_1-y)}{(x_1-x_0)(y_1-y_0)}F(Q_3)+ \frac{(x_1-x)(y-y_0)}{(x_1-x_0)(y_1-y_0)}F(Q_2)+\frac{(x-x_0)(y-y_0)}{(x_1-x_0)(y_1-y_0)}F(Q_4) \quad (1)$$

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To solve this problem, we use ROI Align [17] instead of ROI Pooling, bilinear interpolation to calculate the coordinates of the feature map and cancel the quantization operation. As shown in Figure 3, the feature map needs to be pooled into a 2×2 grid. We assume that the sampling point is 4, and coordinates of four points Q11(x0, y0), Q12(x0, y1), Q21(x1, y1), Q22(x1, y1). Using bilinear interpolation, the coordinates of four points are used to obtain the precise coordinate position of P.

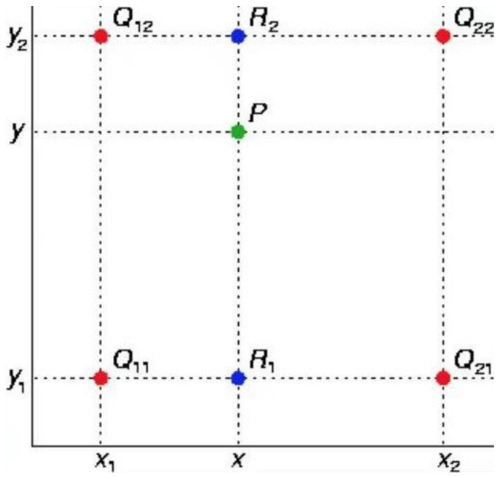

Figure 3. Bilinear interpolation

4. EXPERIMENT

In order to verify the effectiveness of the proposed algorithm, we conduct experiments on the photovoltaic cell data set with indicators such as over-detection rate and recall rate. The experiment is based on the benchmark algorithm framework, using the Ubuntu16.04 system and running on the 2080Ti. The network uses an end-to-end training method. The initial learning rate is 0.0025, and the weight decay is 0.0001. When the number of iterations reach to 30000 and 40,000 iterations, we adjust the learning rate separately, and the maximum number of iterations is 60,000 rounds. We use the trained model to predict the test samples. The predict result is shown in Figure 4. From the figure, we can see that the algorithm can identify the defect type accurately and locate the defect location.

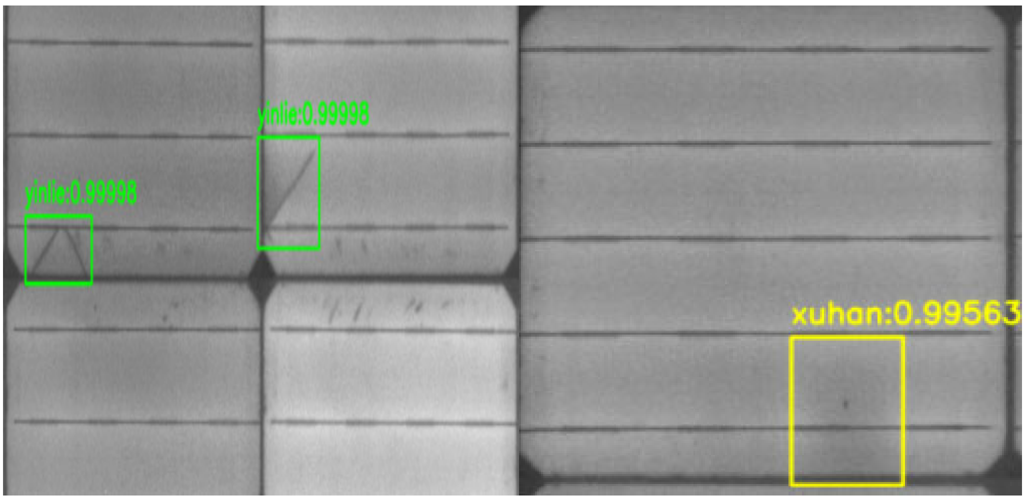

Figure 4. Cell prediction result

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We have made statistics on the accuracy of the test. The over-detection rate represents the proportion of the falsely detected defective images to all the images, and the detection rate represents the percentage of all the images that are detected as defective. The experimental results are shown in Table 1 and Tables 2. It can be seen from the experimental results that the improved faster-rcnn has significantly improved in over-detection rate and detection rate.

Table 1. Detection results of crack defects

Detect type	Faster rcnn	Improved faster rcnn
over-detection rate	14.56%	11.28%
Recall rate	92.31%	97.03%

Table 2. Detection results of virtual welding defects

Detect type	Faster rcnn	Improved faster rcnn
over-detection rate	7.35%	4.14%
Recall rate	94.31%	99.01%

In the detection process, the experiment needs to manually set the threshold, and the detection results below the threshold will not be counted. Therefore, the selection of the threshold plays a key role in the detection process. In order to verify the influence of the threshold, the experiment uses different thresholds to conduct experiments. The experimental results are shown in Figure 5. When threshold increases, the confidence level of the detection results is greater, and the number of false detections gradually decreases. the defective pictures may be ignored, resulting in an increase in the number of missed pictures. Because in the detection process, the threshold value needs to be adjusted many times to achieve a better detection.

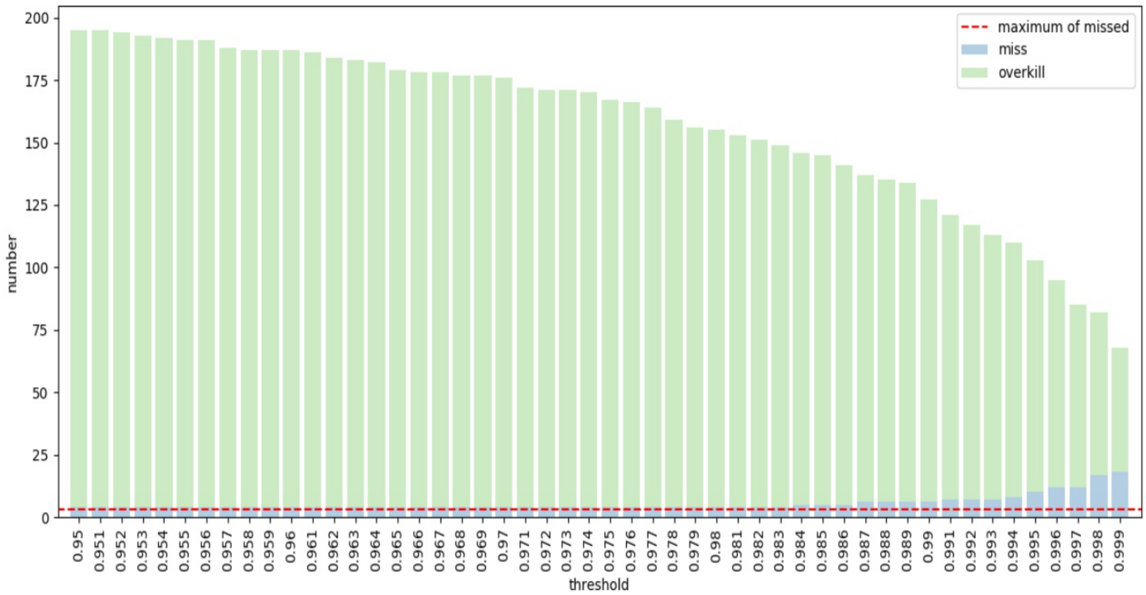

Figure 5. Influence of different thresholds

Finally, we made statistics on the confidence distribution of the prediction results, and the statistical results are shown in Figure 6. Confidence degree indicates the credibility of the test result. If the detection confidence of a defective picture is 0.99, it can be considered that this picture is highly likely to contain defects. Therefore, the certainty of the algorithm to the detection result can be understood through the distribution diagram of the confidence. It can be seen from the figure that most of the test results are concentrated between 0.99 and 1, so we can consider the reliability of the test results to be high.

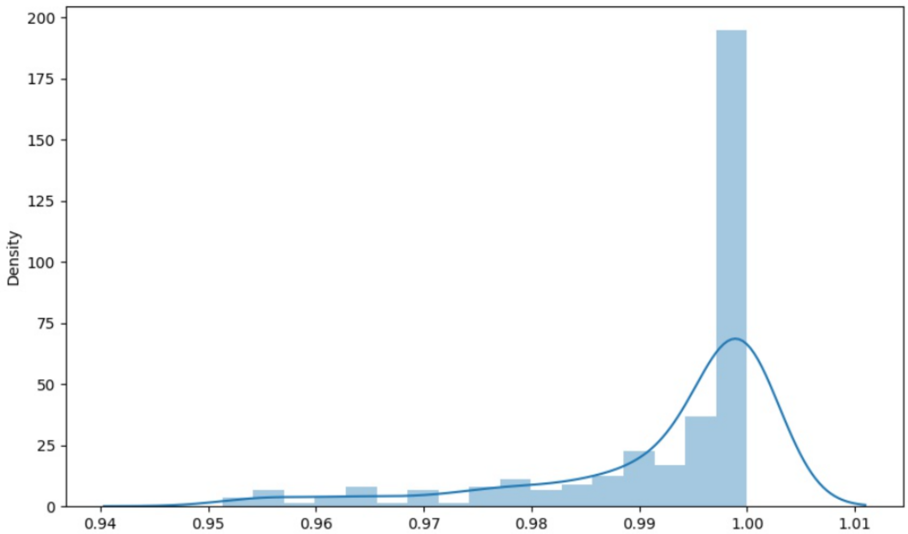

Figure 6. Confidence distribution

5. CONCLUSION

In order to solve the problem of defect location and detection of photovoltaic cells, this paper proposes an improved algorithm based on deep learning, which uses k-means++ to cluster prior boxes to obtain more accurate prior boxes; use a more effective feature extraction network to perform Feature extraction; use ROI Align to cancel the quantization operation and improve the detection accuracy of small objects. Finally, through experiments, the effectiveness of the algorithm is verified on indicators such as over-detection rate and miss-detection rate.

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