

Research on Surface Defect Detection Method of Photovoltaic Power Generation Panels——Comparative Analysis of Detecting Model Accuracy

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Abstract

INTRODUCTION: Research on intelligent defect detection technology using machine vision was conducted to address the challenging problem of detecting and localizing PV defects in photovoltaic power generation system operation and maintenance.

OBJECTIVES: The aim is to improve the accuracy of PV defect detection and enhance the operation and maintenance efficiency of PV power plants.

METHODS: In this paper, three detection methods such as image processing based detection, traditional machine learning based detection, and deep learning algorithm based detection are discussed and compared, and analyzed respectively. It is finally concluded that the deep learning based detection is more efficient in comparison. Then further analysis and simulation experiments are done through several detection algorithms based on deep learning.

RESULTS: The experiment yields a high accuracy of the detection model based on the Faster-RCNN algorithm. Its mAP value reaches 92.6%. The detection model based on the YOLOv5 algorithm reaches a mAP value of 91.4%. But its speed is as much as 7 times faster than the model based on the Faster-RCNN algorithm.

CONCLUSION: Comprehensive speed and accuracy index. Combining the needs of PV defect detection in the operation and maintenance of PV power generation systems with the results of simulation experiments. It is concluded that the detection model based on the YOLOv5 algorithm can provide better detection capability. Modeling with this algorithm is more suitable for PV defect detection.

Keywords: Computer vision, Deep learning, Solar panels, Deep learning, Photovoltaic defects

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1. Introduction

In the development of PV industry, PV defects have always been a problem affecting PV power generation. Due to long-term exposure to the natural environment, PV modules are susceptible to various external factors, such as temperature changes, wind and rain erosion, rocks and stones. Or, they may be blocked by foreign objects, resulting in uneven

heating of the internal components, leading to high-temperature burnout of the modules. All of the above reasons are prone to PV module defects. Common PV defects include cracks, broken grids, black cores, thick lines and hot spots, etc. The pattern of hot spots and cracks is shown in Figure 1 below. The formation of PV defects in PV power generation panels seriously affects the quality of the heating panels and reduces the efficiency of power generation. According to

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authoritative statistics, PV defects can reduce the actual service life of PV modules by at least 10% [1-2]. Therefore, it is necessary to detect the presence of defects in an effective way and then repair or replace them.

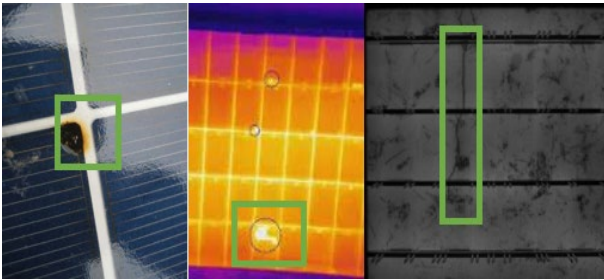


Figure 1. Defects on photovoltaic panels

Photovoltaic power stations are mostly constructed in deserts, barren mountains, lakes and other places that are not easily accessible by human labor. The traditional manual hand-held scanner detection method is inefficient, heavy workload, low accuracy and serious economic expenditure. With the development of technology, the way based on image processing is more simple and efficient. It can greatly reduce the labor intensity and labor time of operation and maintenance personnel, liberate manpower and save costs. This paper takes PV defect detection as the center of the discussion. First of all, the common photovoltaic defect detection methods are analyzed and discussed, and then further control verification is done through simulation experiments to compare the advantages and disadvantages of different detection methods.

2. Image Processing-Based Detection

Before machine learning was widely used, image processing-based target detection technology was the main detection method. Image processing-based detection is mainly divided into two parts: image preprocessing and defect detection. Image preprocessing includes algorithms such as image denoising and image segmentation, which is the preliminary work of defect detection. Defect detection is mainly accomplished using image feature extraction or template-matching algorithms.

2.1. Image Preprocessing

Image preprocessing is usually needed to deal with noise during image processing. The preprocessing methods can be categorized into two types: air domain and frequency domain. An intuitive approach is to use low-pass filters, such as sliding average window filters and Wiener linear filters, to efficiently remove noise in the high-frequency portion of the image because the frequency spectrum of an image is usually limited to a finite region. The simplicity and low

computational cost of the null domain filtering method makes it more suitable for real-time processing. Baozhu Guo^[3] used various algorithms such as non-uniform stretching and adaptive median filtering to correct the image and achieved the effect of increasing the contrast of infrared image and filtering out the pretzel-like noise.

2.2. Defect Detection

Feature extraction aims to extract key information from images, and the quality of feature extraction directly affects the subsequent feature point matching, template matching and computational efficiency. Typical feature extraction methods include those based on different characteristics such as texture, color and shape.

The task of template matching is to determine the location of a specific object or pattern in an image, and the accuracy of the matching is crucial for defect detection. Common matching methods include those based on elements, grayscale information and shape. In surface defect detection, shape-based matching methods are commonly used to detect defects. The process of this method includes determining the target region, creating a standard template, and matching the test image with the standard template, and finally classifying and recognizing the defects by the matching results.

Literature^[4] in order to reduce the random noise and non-uniformity interference, proposed a processing method based on the B-spline least squares fitting of gray scale histogram, which can suppress the infrared image noise and improve the accuracy of detecting defects. Literature^[5] proposes a defect localization method based on slope and length constraints for photovoltaic array infrared thermal imaging image and visible image alignment. The experimental results show that the final successful and accurate matching results, realizing the localization of photovoltaic defects.

3. Traditional machine learning-based detection

3.1. Defect Detection

SVM is a binary classification model proposed by Vapnik^[6] in 1995 based on statistical learning theory. Its core idea is to find the maximum interval hyperplane while correctly classifying the training data. SVM realizes linear or linear approximate classification by mapping the low-dimensional input space to the high-dimensional feature space. It has unique advantages in solving problems such as small samples and pattern recognition, and has been successfully applied to photovoltaic defect detection.

Yannan Yang^[7] extracted two features of relative maximum temperature and relative average temperature of sub-image block and detected the sub-image block containing defects using SVM classification model, and the detection success rate reached 94.47%. Literature^[8] similarly takes the two features of maximum temperature and average temperature and successfully detects the PV defects using

SVM classification model, and the success rate also reaches more than 90%.

3.2. Convolutional neural network (CNN) based detection

CNN (convolutional neural networks) network structure is shown in Fig. 2. It mainly consists of convolutional layer, pooling layer, fully connected layer, nonlinear unit, loss function and other parts. Among them, convolutional layer and pooling layer are the key components. The convolutional layer can effectively reduce the computation and storage requirements. The pooling layer reduces the dimension of the feature map by down-sampling and prevents overfitting. The activation function introduces a nonlinear mapping and improves the feature representation of the network. The fully connected layer, usually located at the end of the network, maps learned features to the sample labeling space for classification or regression tasks.

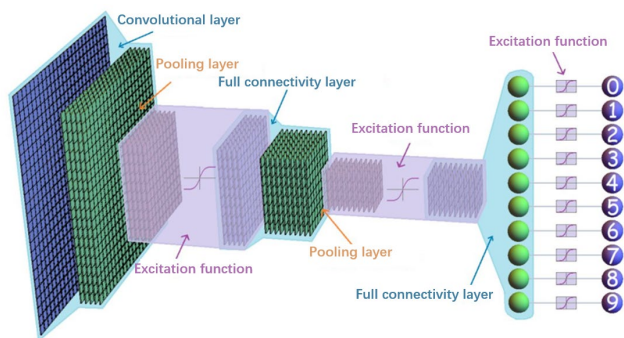


Figure 2. Common structures of convolutional neural networks

Literature^[9] uses two convolutional layers, two pooling layers, two fully connected layers and one softmax layer. At the same time, in order to prevent the results from overfitting due to small data samples, a dropout layer was added to the model for PV defect detection. The final validation accuracy reaches 90%. Literature^[10] constructed a deep convolutional self-coding network model. The model automatically learns and extracts effective features from small sample images and improves the recognition rate by 7.9% over the traditional CNN model.

4. Deep learning-based detection

At the current stage, deep learning-based target detection algorithms are mainly categorized into two main groups: one-stage algorithms and two-stage algorithms. Among the two-stage algorithms, especially the Faster-RCNN algorithm has the highest accuracy. Same as the detection under PASCAL VOC 2007 dataset, Faster-RCNN algorithm has the highest

mAP value of 78%. It is 10 points higher than the second Fast-RCNN, which is far ahead. Among the one-stage algorithms, the representative algorithms are SSD algorithm and YOLO series.

4.1. Faster-RCNN based detection

In 2015 Ren S et al^[11] proposed the Faster-RCNN algorithm. Its model architecture is shown in Figure 3 below. The RPN (Region Proposal Networks) network is designed on the basis of Fast RCNN network to obtain Region proposals inside the whole network to realize the real end-to-end.

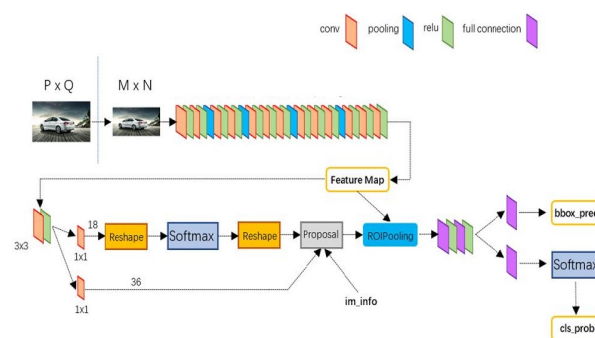


Figure 3. Faster-RCNN network structure diagram

It first extracts image features using convolutional basis network. Secondly, multiple candidate target regions are generated in the Region Extraction Network. Then Detection Head performs target classification and bounding box regression on these regions. Finally, activation and loss functions are used to train the network. These components collaborate to enable Faster R-CNN to detect targets in images efficiently and accurately.

Literature^[12] combines migration learning, improved feature extraction network model based on Faster-RCNN. The model improves the Faster-RCNN's poor detection of small targets and achieves an average detection accuracy of 97% on the test set. Literature^[13] combines Faster-RCNN with Spot FPN multi-scale feature learning module. The detection of small targets in the model can be improved by adding the Spot FPN structure, and the accuracy of the model can be improved by using the auxiliary loss function and the primary loss function to predict together, and its average accuracy is improved by about 3% compared to the pre-improvement period.

4.2. Detection based on YOLO series algorithms

YOLO series algorithms have been widely used in practical detection, this paper gives a detailed introduction to YOLOv5 and YOLOv7, which are the best evaluated at this stage.

(1) YOLOv5: The YOLOv5^[14] model is divided into four parts: input, Backbone, Neck, and output [15,16]. Its basic structure is shown in Figure 4 below. The input side adopts adaptive anchor frame computation, which automatically adapts to the image zoom and reduces the amount of model computation. Backbone adopts the Focus structure to reduce the information loss in the downsampling process, and draws on the CSP structure of CSPNet^[17] to enhance the learning ability of convolution. The Neck side adopts the structure of FPN+PAN+CSP, which strengthens the feature fusion. The output side adopts GIOU_Loss as the loss function of the bounding box, and the weighted NMS is used to filter the bounding box to enhance the detection ability of occlusion and overlapping targets.

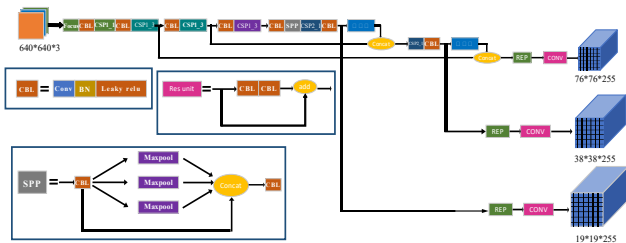


Figure 4. YOLOv5 algorithm structure

Feng Hong et al^[18] utilized the YOLOv5 + ResNet algorithm model for the detection of defects with a mAP@0.5 value of 91.7%. The detection speed reaches 36 frames per second. It is summarized that YOLOv5 algorithm model is the optimal detection algorithm model that combines detection accuracy and detection speed.

(2) YOLOv7: YOLOv7 leads current mainstream target detectors in detection speed and accuracy in the range of 5 FPS to 160 FPS. Compared to the YOLOv5 algorithm, its backbone network for feature extraction incorporates an extensible Efficient Layer Aggregation Network, E-ELAN^[19], a structure that allows the deep neural network to accelerate model convergence by controlling the gradient path.

E-ELAN enhances the learning capability of the original network by expanding, transforming, and fusing bases, avoiding the problem of infinite stacks of computational units that may destabilize the steady state of the gradient path. In addition, the E-ELAN+MP structure constructs a downsampler through the combination of maximum pooling and BConv units, which further enhances the feature extraction capability of the backbone network and achieves the optimal balance between speed and accuracy.

4.3. Detection based on SSD algorithm

SSD is one of the classical single-stage multi-frame target detection algorithms. It consists of three main parts: feature extraction network, target detector, and non-extremely large value suppression. First, the feature extraction network uses

6 feature layers of different scale sizes to extract the input image to generate a feature map. Then the target detector uses 2 sets of convolution kernels to convolve each feature map to generate prediction frames with position and category information to achieve multi-scale target detection. The prediction frames with category information are scored and filtered by the Non-Maximum Suppression (NMS) algorithm, and the prediction frames with category confidence greater than or equal to the threshold (0.5) are taken as the final detection results^[20]. The network structure of SSD is shown in the following Figure 5.

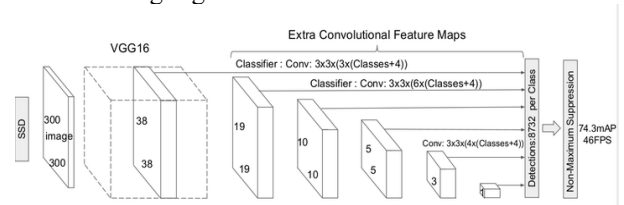


Figure 5. SSD algorithm structure

4.4. Comparison of Current Detection Models

The characteristics, advantages, and disadvantages of the above various detection models have been analyzed and summarized and the results are presented in Table 1.

Table 1. This is a legend. Caption to go above table

Methods	Models	Strengths	Weaknesses
Image Processing	Feature Extraction Template Matching	Robustness is better and can be verified with fewer images.	The detection process is more complicated and cannot perform automatic feature extraction.
Machine Learning	SVM Model CNN model	Doesn't need a huge number of images for training, simple processing algorithm.	Detecting multiple defects does not play its performance.
Faster-RCNN	FCN Model	Can receive images of arbitrary size for detection; can realize pixel-level segmentation on input images.	Insensitive to the detail information in the image, the model convergence speed is slow.

SSD	SSD Model	Fast speed, good results for both large and small targets.	Feature layers of different categories cannot share information;
YOLOv5	YOLOv5 Model	Multi-model structure, high flexibility, fast detection speed.	Model computation increases and positive and negative sample imbalance; accuracy needs to be improved.
YOLOv7	YOLOv7 Model	Realizes the best trade-off between speed and accuracy of the training process.	The feature extraction network generates some redundant parameters in the training process.

Comprehensively comparing several algorithmic models, it is found that the deep learning-based detection model can continuously learn the features of PV defects through convolutional operations, and finally achieve classification or regression on visual tasks. In terms of detection accuracy and speed, it is better than the detection model based on image processing and the detection model based on machine vision. However, there are many PV defect detection models based

on deep learning, and no scholars have been found to analyze and compare them. This paper for the first time will be applied to a photovoltaic defect detection deep learning model for simulation experiment comparison.

5. Simulation Study of Deep Learning-Based Detection Models

After reviewing the experimental comparisons of several scholars, it is concluded that among the algorithms based on depth learning, the three detection models Faster-RCNN, SSD, YOLOv5, and YOLOv7 have excellent performances, respectively. However, for these models, no scholars have been found to compare and analyze them. So in this paper, we conduct an experimental comparison of these three deep learning-based detection models with the same dataset, and the experimental process and results are as follows.

5.1. Comparison of Current Detection Models

(1) Producing the dataset. In this paper, a total of 4500 photovoltaic defect datasets are organized and obtained, these images cover a variety of photovoltaic defect situations in real scenes. Including cracks, broken grids, black cores, thick lines, and hot spots. As shown in the Figure 6 below. These defect types are important in the quality control and inspection of PV modules. They are divided into training set, testing set, and validation set according to 8:1:1.

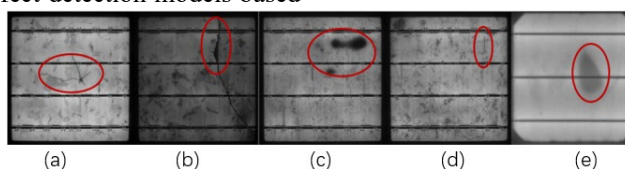


Figure 6. Different defects in the component (a) Cracks; (b) Broken grids; (c) Black core; (d) Thick lines; (e) Hot spots

(2) Experimental environment and parameter settings. In this study, the neural network framework was built using Pytorch 1.11, the experimental platform operating system was Windows 10, the CPU model was Intel i5-12400F, and the GPU model was NVIDIA GTX3060. batch size was set to 8, Epoch was set to 100 times, and the network parameters were adjusted using the stochastic gradient descent method SGD. The network parameters are tuned using the stochastic gradient descent method SGD.

5.2. Comparison of Current Detection Models

The mAP, Precision, and detection speed are used as evaluation metrics, while the performance of the algorithm model is referenced through the loss function.

For the target detection algorithm, the mean Average Precision (mAP, mean Average Precision) is used as the evaluation criterion of algorithm accuracy, and the calculation of mAP is closely related to IoU. The calculation of IoU of the anchor frame and the rear frame is shown in Equation 1, where b_{gt} denotes the position coordinate information of the real frame and b_{pred} denotes the position coordinate information of the predicted frame

$$IoU(b_{pred}, b_{gt}) = \frac{Area(b_{pred} \cap b_{gt})}{Area(b_{pred} \cup b_{gt})} \quad (1)$$

The IoU of the default frame and the true frame is calculated and then the default frame is categorized as a positive or negative example based on the set IoU threshold. In the image, for each category, there will be True Positive (TP, True Positive) which is the positive example with correct prediction, False Positive (FP, False Positive) which is the

positive example with wrong prediction, True Negative (TN, True Negative) which is the negative example with correct prediction, and False Negative (FN, False Negative) which is the negative example with wrong prediction, thus the accuracy can be calculated as shown in Equation 2. Negative examples, from which the accuracy can be calculated, the calculation is shown in Equation 2.

$$\text{precision} = \frac{TP}{TP+FP} \tag{2}$$

The loss function is used to estimate the degree of inconsistency between the model's predicted value $F(x)$ and the true value Y . It is a non-negative real-valued function, and the smaller the loss function is, the better the robustness of the model is. In this paper, we compare the stability of the model concerning the loss function of three models.

5.3. Experimental results

In the migration training of the detection models for PV defects in PV modules with thermal infrared images, the specific test results and performance of the three detection models on the validation set are shown in Table 2.

Table 2. Comparison of results of PV defect detection algorithms

Method	Structure	Speed(ms)	Accuracy value (%)	Accuracy mAP@0.5(%)
Faster-RCNN	ResNet-101	220	93.5	92.6
SSD	VGG16	120	85.6	88.3
YOLO v5	CPSDarknet 53	40	91.1	90.5
YOLO v7	ELAN	32	93.0	91.4

Through the comparative analysis in Table 2, the four deep learning detection models perform as follows in terms of detection accuracy: the Faster-RCNN model achieves the highest 92.6%, the YOLOv7 model is slightly lower at 91.4%, and the SSD model has the lowest detection accuracy at 88.3%. In terms of detection speed, the YOLOv7 model is the fastest, which is more than three times faster than the SSD model and more than seven times faster than the Faster-RCNN model. Notably, in terms of hardware resource usage, the YOLOv5 and YOLOv7 models consume less relative to the other two models.

In addition, we imported the loss function data of the four models into Origin software for the loss function descent curves, which are shown in Fig. 7.

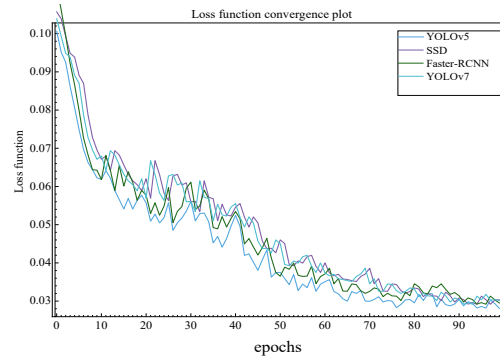


Figure 7. Loss function convergence plot

According to Figure 7, all four detection models have loss functions that converge sufficiently without showing signs of overfitting or underfitting. The YOLOv5 detection model, in particular, has a more obvious and smooth convergence compared to the other three models. While the other three models show similar results, the Faster-RCNN detection model displays relatively larger fluctuations. From observing the loss function curves, it is evident that the YOLOv5 model has a quicker decrease in the loss value and displays higher learning efficiency. This suggests that the algorithm can adapt to the training data more rapidly and find better parameter settings, which ultimately improves the model's performance. Additionally, the YOLOv5 algorithm model's loss function curve is smoother, showing a relatively smooth downward trend with no significant fluctuations or oscillations. This indicates that the model is more robust to changes and noise in the training data, and can optimize the model parameters stably during the training process, enhancing the model's reliability. Overall, the YOLOv5 model outperforms the other three models.

5.4. Experimental Summary

When evaluating the performance of four different detection models, the YOLOv5 model stands out in several important areas. In terms of hardware resource consumption, detection accuracy, and detection speed, the YOLOv5 model achieves satisfactory results. Notably, it provides faster detection speed while reducing the consumption of hardware resources, maintaining higher accuracy, and exhibiting more stable robustness. This makes the YOLOv5 model a more appealing option for practical applications, particularly for tasks that require high efficiency and reliability. Overall, all four models perform well in terms of stability, but the YOLOv5 model has clear advantages in key areas.

6. Conclusion

The photovoltaic (PV) industry continues to grow in the global power supply. Therefore, more efficient PV defect detection methods are of great practical significance for the

development of the PV industry. This paper analyzes several common machine vision based methods for detecting PV defects. It is concluded that the deep learning based detection method is more efficient and low cost. Then this paper proposes for the first time to compare the deep learning based PV defect detection model for simulation. From the results, the YOLOv5 based detection model has more than 90% high accuracy while taking into account the powerful detection speed. It is also lower than other detection models in the utilization of hardware resources. After combining the above advantages, the YOLOv5-based inspection model is the most superior inspection model, which is more suitable for PV defect detection applications.

Despite the research results of our study, we have to honestly discuss the limitations of the study. First, the size of the dataset we used is relatively small, which may affect the generalization performance of the model. In addition, our study has not been tested in real PV sites, so further validation of the performance of our model in real-world applications is still needed.

Future research directions include extending the dataset to better represent the diversity of PV sites and further optimizing the training strategy of the model to improve the performance. In addition, we can also consider applying other deep learning techniques, such as attention mechanisms or transfer learning, to PV defect detection to further improve the detection accuracy.

In summary, our research brings important insights and innovations to the field of PV defect detection, and the successful application of the YOLOv5 algorithm provides strong support for practical applications. However, there are still many potential research opportunities and challenges waiting to be explored and solved. We expect that future work will continue to advance the field.

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