Research Progress on Deep Learning Based Defect Detection Technology for Solar Panels

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Abstract

INTRODUCTION: Based on machine vision technology to carry out photovoltaic panel defect detection technology research to solve the photovoltaic panel production line automation online defect detection and localization problems.
OBJECTIVES: The goal is to improve the accuracy of defect detection on PV cell production lines, increase the speed of defect detection to meet real-time monitoring needs, and improve production efficiency.
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. Finally, it is concluded that deep learning based detection methods are more effective in comparison. Then, further analysis and simulation experiments are done by several deep learning based detection algorithms.
RESULTS: The experimental results show that the YOLOv8 algorithm has the highest precision rate and maintains good results in terms of recall and mAP values. The detection speed is all less than other algorithms, 10.6ms.
CONCLUSION: The inspection model based on yolov8 algorithm has the highest comprehensive performance and is the most suitable algorithmic model for detecting defects in solar panels in production lines.

1. Introduction

With the increased global attention to clean energy, the development and utilization of clean energy, represented by solar energy, has been emphasized by various countries. Because of its high utilization rate, high efficiency and low cost, solar power will occupy an important position in the future energy structure.

In the development of solar energy utilization, solar photovoltaic power generation is the fastest growing and most dynamic research field in recent years. In order to achieve the goal of carbon neutrality, solar power generation will become a strategic industry prioritized by the state, and photovoltaic companies will continue to expand the scale of production [1]. Solar panels may be improperly operated during the production process, resulting in defects such as broken grids, missing corners, color differences, dirt, cracks and other defects on their surfaces, which will not only reduce the service life of solar panels, but also affect their work efficiency [2]. Therefore, the defect detection of solar panels has become an important guarantee for the reliable operation of solar panels, and the study of defect detection methods for solar panels has important engineering practical significance. Table 1 summarizes the types of solar panel surface defects, visual effects, causes and common defect pictures.

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Table 1. Common defects in solar panels

Defect category	Defect Name	Visual Characteristics	Cause of formation	Image
Shape defects	Broken, crack, broken grating	Defective in shape compared to standard films	Mis-cutting, collision	
Color defects	Abnormal color defects	Color anomales compared to standard films	Uneven chemical reaction	
Texture defects	Spots, fingerprints, wheel marks	Differences in brightness compared to standard films, with Spotty	Human error, machine stress	

Existing solar panel surface defect detection methods according to the different materials of the panel and the differences in detection means, mainly divided into artificial visual method, physical detection methods and image detection methods of three types, commonly used defect detection methods shown in Figure 1.
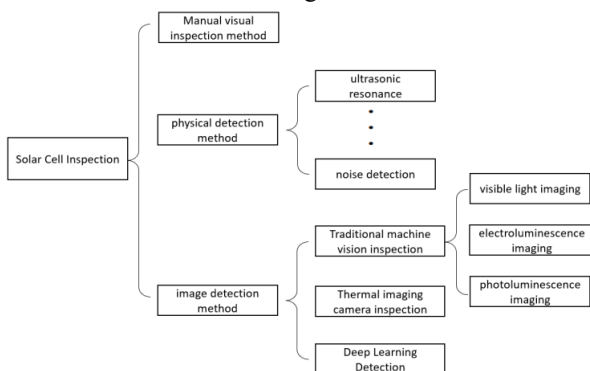

Figure 1. Commonly used defect detection methods for cells

Artificial visual method is through the naked eye on the solar panel surface observation and detection, this method of detection rate is low, generally between 50% and 70%. Physical inspection methods through specific physical means of solar panel surface inspection, can be more accurate to find defects, the general detection rate of 70% to 80%. Image inspection method is to analyze and process the image of the solar panel surface through computer vision technology, so as to find defects. This method can be automated, efficient detection, reducing the impact of subjective factors. Generally speaking, the detection rate of the image inspection method is above 80% and can even reach above 85%.

This paper investigates the solar panel defect detection technology. Firstly, it introduces the types of faults in the production of solar panels and the causes of the faults; secondly, it summarizes and compares the traditional solar panel defect detection methods; it focuses on detailing the research results of the existing solar panel detection methods; finally, it summarizes the paper.

2. Traditional solar panel defect detection technology

2.1. Physical detection methods

Physical inspection methods for solar panel defect detection mainly utilize the physical properties of the solar panel surface, such as changes in acoustic waves, vibration, electromagnetic fields, and so on, to determine whether there are defects. These methods can improve the quality of solar panels by detecting defects and handling them in time during the production process.

Tsuzuki et al. [3] Using acoustic wave technology to detect the presence of cracks in solar panels, this detection method triggers proper resonance of solar panels to generate acoustic waves, and then the frequency of the acoustic waves is analyzed and compared with the standard frequency to determine the presence of cracks on the surface of solar panels; Esquivel [4] By increasing the light intensity on the surface of the solar panel so that the cracks and defects can be reflected to another plane, the presence of defects can be determined if there is image distortion; Sawyer et al. [5] Detection using laser scanning technique by showing the continuity of resistance in crystalline silicon with forward bias of laser scanning, if cracks are present, the resistance will be discontinuous; Chen et al. [6] used noise-based detection, which utilizes the low-frequency noise of crystalline silicon solar panels to correlate with reliability by comparing the difference in noise between defective and non-defective solar panels, thus determining whether there is a defect or not.

Physical inspection methods can detect defects on the surface of solar panels through specific physical means, which can find defects more accurately and have higher detection rate and accuracy. However, these methods require the use of specific testing equipment and instruments, the cost is high, and the operation is more complex, low detection efficiency, is not suitable for large-scale production inspection. Physical inspection method is mainly for specific physical parameters for detection, for some types of defects may not be able to effectively detect, has certain limitations.

2.2. Traditional machine vision-based solar panel defect detection

Image-based solar panel surface defect detection methods have obvious advantages over physical detection methods in terms of efficiency and accuracy. This chapter summarizes traditional machine vision based defect detection methods

from the perspective of image processing, feature extraction and classification algorithms.

Image processing

Starting from the traditional feature image processing algorithm, when there is too much interference or not enough useful information in the acquired infrared image, preprocessing is required to eliminate noise and highlight useful features. Traditional image preprocessing methods for solar panels include grayscaling, noise reduction, image binarization and edge detection, which can effectively improve the image quality and provide a better data base for subsequent tasks such as defect detection, classification and recognition.

Wang Y et al. [7] proposed a weighted fusion filtering algorithm that combines Gaussian filtering and mean filtering, which can both protect the local edge features of the image and reduce the image noise well to meet the requirements of high-definition images for subsequent image processing.Akram et al. [8] Proposed image filtering, color quantization and edge detection solar panel infrared image processing scheme, to achieve the infrared image of serious and minor defects in the region of edge localization.

Feature extraction

Image feature extraction is to extract key information from the original image to characterize the target. For solar panel defect detection, traditional feature extraction methods mainly include steps such as edge detection, texture analysis, color feature extraction and shape feature extraction. These methods can effectively extract the surface defect information of solar panels and provide an accurate data base for subsequent tasks.

Liu Chengcheng et al. [9] proposed a method that combines the Hough transform and Canny edge detection to remove the surface gridline interference and reduce the interference of the gridline for the detection process, which in turn improves the accuracy of defect detection. Zhou Qi et al. [10] Aiming at the solar cell appearance defects and color differences, through an in-depth analysis of the battery appearance characteristics, the Canny edge detection algorithm is improved, and a series of solar cell defect discrimination algorithms based on the HALCON image processing software are designed to improve the processing of fault details by photovoltaic infrared image processing technology.

Feature extraction

Traditional machine vision methods use manually extracted feature information to train classifiers to correctly recognize surface defect classes. The most widely used classification algorithm for solar panel defect detection is the Support Vector Machine (SVM) algorithm.SVM is a typical binary classification model whose basic model is the interval-maximized linear classifier that can handle complex nonlinear classification problems.

Liu Lei et al [11] used an erasure algorithm to remove the electrodes and gates from the acquired images, extracted features from the remaining defective targets, and designed the corresponding SVM classifiers for classification, which can realize the detection and identification of defects such as broken gates, chipped corners, cracks, chipped edges, and leaking pulp, etc. Deitsch S et al [12] proposed a general framework for training SVMs and CNNs on high-resolution solar cell wafer EL test images. Demant [13] proposed a support vector machine based method for detecting surface defects on solar cell wafers. The samples labeled with cracks and non-cracks are obtained, and the feature vectors are extracted and fed into SVM for training.

3. Deep Learning Based Defect Detection in Solar Panels

Deep learning can quickly and accurately identify various types of defects using its powerful feature extraction capability by simply allowing the network model to be network trained on the dataset. Therefore, deep learning-based solar panel defect detection techniques are widely used in various defect detection tasks. Deep learning-based target detection algorithms can be mainly categorized into Two-stage target detection and One-stage target detection, as shown in Figure 2. Common Two-stage target detection algorithms include R-CNN, Fast R-CNN and Faster R-CNN. Common One-stage target detection algorithms are YOLO series, SSD and so on.
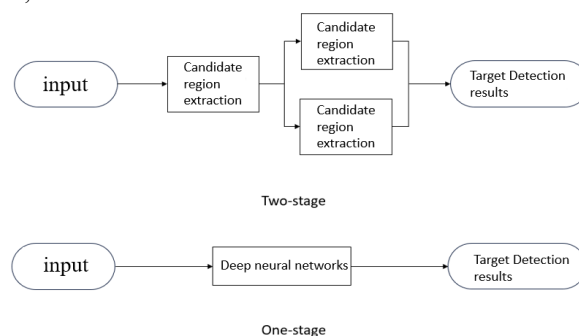

Figure 2. Deep learning based target detection algorithm

In this paper, the deep learning based surface defect detection method is compared with the traditional image processing based surface defect detection method as shown in Table 2.

Traditional image processing-based defect detection methods rely on image processing techniques such as filtering and edge detection to extract defect features, while deep learning-based defect detection methods utilize deep neural networks to automatically identify and differentiate between various types of defects with higher accuracy and flexibility.

This chapter summarizes defect detection algorithms commonly used in defect detection tasks.

Table 2. Comparison between traditional image processing based defect detection methods and deep learning based defect detection methods

Element	Traditional image processing based defect detection methods	Deep learning based defect detection method
Extraction process	Manual extraction of features from raw data	Automatic feature extraction for networks
vantage	Generally faster and more interpretable detection process	Relatively high accuracy, applicability and flexibility
drawbacks	Relatively low accuracy, lack of flexibility and reliability	Suffers from overfitting and lack of generalization ability

3.1. Faster R-CNN

Faster R-CNN is based on Fast R-CNN and introduces the concept of region proposal network (RPN) to replace the selective search algorithm (selective search) to generate candidate regions, which makes the target detection task significantly improved in terms of accuracy and speed. The structural model diagram is shown in Figure 3.
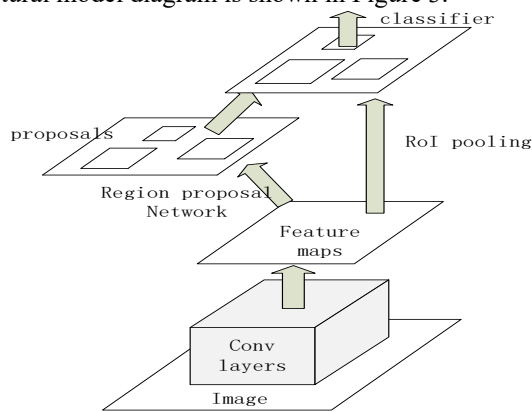

Figure 3. Faster R-CNN model structure

Ishin Equivalent [14] Introducing the residual attention module RCA in Faster R-CNN effectively suppresses the influence of complex background and inputs it into the network for localization detection and identification, the model can effectively detect the surface defects of panels and meet the needs of actual photovoltaic cell production and manufacturing. Aiming at the shortcomings of traditional solar cell inspection methods such as long detection time and low detection accuracy, Lu Donglin et al. [15] took Faster R-CNN as a framework, incorporated a multi-scale detection network based on FPN, and applied GA-RPN structure to realize the detection of small target defects on solar cell wafers. The mean average accuracy and detection speed of the improved method are shown to be upgraded compared

with the original Faster R-CNN algorithm through experimental results.

3.2. YOLO

YOLO is an algorithm for target prediction based on global image information, which is a target detector that uses features learned by deep convolutional neural networks to detect objects. Compared with the Faster R-CNN algorithm, YOLO algorithm treats the object detection problem as a regression problem, and directly regresses the position of the bounding box and the class it belongs to in the output layer, which greatly improves the detection speed, but the detection accuracy is slightly weaker.YOLO series of algorithms have been updated and iterated successively through the YOLO, YOLOv2, YOLOv3, etc., and have been developed into the latest YOLOv8 version. The latest YOLOv8 version, YOLOv8 model structure is shown in Figure 4.
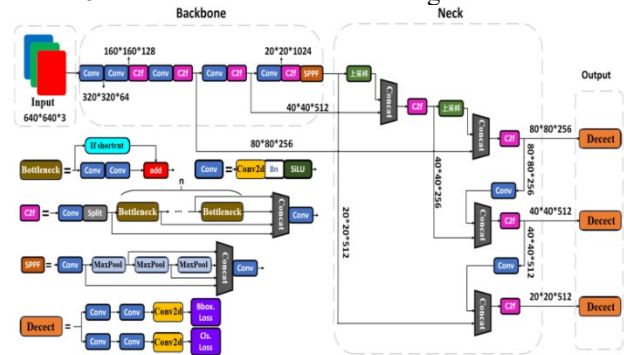

Figure 4. YOLOv8 model structure

Tian et al. [16] The YOLOv3 neural network model was improved by borrowing the dense connection mechanism of DenseNet neural network, and the improved network model N-YOLOv3 recognition accuracy, missed detection rate, false detection rate, and detection time were all improved.

Gao Tianyang et al. [17] The YOLOv3 algorithm was analyzed in depth, and the model was improved by optimizing the learning rate configuration and non-maximal value suppression, etc. The improved algorithm can achieve 89.39% average accuracy and 91.93% single-category accuracy for the identification of hidden crack defects with a high incidence rate.

In order to improve the accuracy and speed of solar panel defect detection, Shuqing Wang et al. [18] improved a data enhancement method with dynamic feedback multi-scale training at the input of YOLOv5 model and used ELU activation function to replace the activation function in the backbone network, which is of practical application for the surface quality specification of solar cell panels.

Zhou Ying [19] et al. proposed a solar cell defect generation algorithm that fuses multiple receptive fields and attention to generate high-quality defect images for data enhancement, and perform mean filtering on the generated images, which, combined with the training of the YOLOv7 detection model,

resulted in a high mean average accuracy mean value for the three types of defects, namely, solid black, shadows, and hidden cracks.

Now with continuous innovations, YOLOv8 becomes the latest and most advanced YOLO model, which builds on previous successful YOLO versions with improvements in backbone network, detection header, and data enhancement to further improve the performance and generalization of target detection for object detection, image classification, and instance segmentation tasks.

3.3. SSD

The SSD algorithm borrows both the idea of YOLO grid and the anchor mechanism of Faster R-CNN, which can obtain the position of the target efficiently and accurately at the same time of fast detection.The feature pyramid-based detection is added in the SSD algorithm, which is aimed at extracting the multi-scale features to accurately detect the objects at different scales.

Xu Xing et al. [20] Optimally trained convolutional neural network models and model fusion methods are used to realize the purpose of identifying solar panel faults. Based on SSD Deep Learning Target Detection Algorithm Deep Learning Target Detection Algorithm implements solar cell panel defect localization detection and verifies the excellent performance of deep learning in the solar cell defect classification task. Zhong Yongsong [21] In the SSD backbone network VGG16 fused six CBAM (Convolutional Block Attention Module, CBAM) attention mechanism module corresponds to its output of six scales of feature maps, respectively, to enhance the algorithm's ability to multi-scale feature extraction, the results show that the improved SSD algorithm detection accuracy is higher, the model training speed is faster.

One-stage target detection algorithms are algorithms based on regression problems, which are more dominant in detection speed; Two-stage target detection algorithms are algorithms based on candidate regions, which are more dominant in detection accuracy. With the advancement of deep learning technology, the accuracy of many one-stage target detection algorithms has approached or exceeded that of the two-stage model, which is also developing in the direction of deeper and more efficient to improve the accuracy and speed of the model. Therefore, this paper analyzes and summarizes the advantages and limitations of various mainstream algorithms, as shown in Table 3.

Table 3. Overall analysis of defect detection algorithms

Typology	Arithmetic	Network	Vantage	Limitations
Two-stage	Fast R-CNN	VGG16	Reduced computational complexity and reduced size of space required for training	Slow prediction rate and poor real-time
	Faster R-CNN	ResNet 101	Reduces model calculations and greatly improves detection speed	Less real-time
One-stage	YOLOv1	VGG16	Algorithm based on regression problems with good generalization and migration capabilities	Low detection accuracy and poor detection of small targets
	SSD	VGG16	Enhanced accuracy for small target detection, adaptable to multiple scale target detection	Low detection accuracy and poor detection of small targets
	YOLOv3	Darknet-53	Optimized loss function to improve detection of small targets	Complex models and long computation times
	YOLOv5	Modified CSP v5	Improved detection of small targets, fast detection speed and high flexibility	Still a bottleneck for small target detection
	YOLOv7	Darknet-53	Faster convolutional operations and smaller models capable of detecting	There is still room for improvement in lightweighting

| | | fine objects | |

| YOLOv8 | Darknet-53 | Achieved further lightweighting for improved performance and flexibility | -- |

4. Experiments with Mainstream Deep Learning Algorithm Models

In order to explore the detection ability of the above deep learning algorithm models in the actual detection of solar panel defects, after reviewing and analyzing the current mainstream algorithms, six representative algorithms, namely, Faster R-CNN, SSD, YOLOv3, YOLOv5, YOLOv7, and YOLOv8, are selected for experimental comparison.

4.1. Experimental setup

The computer configuration and operating environment for the experiments of this study are: image processor GPU: NVIDIA GeForce RTX 4060 Ti (8G); central processor CPU: 13th Gen Intel(R) Core(TM) i5-13600KF 3.50 GHz; computer memory: 32G; operating system: Windows 10 Professional Edition ; Programming language: Python (version 3.8); Deep learning framework: PyTorch.

The dataset used in this paper is derived from the publicly available dataset repository, a total of 3800 solar panel defect datasets are compiled based on the research content and requirements, these images represent five common types of PV defects including cracks, broken grids, black cores, thick lines and hot spots. The images are 640x640 pixels in size and are divided into training, testing and validation sets according to 8:1:1.

In this experiment, five types of defects, namely, cracks, broken grids, black cores, thick lines and hot spots, are targeted for detection. The six algorithms are trained using the same parameter configuration with the initial learning rate set to 0.0003, batch-size set to 8, and the maximum number of iterations set to 200.

4.2. Performance assessment indicators

In order to test the performance of the experimental model, Precision, Recall, Average Precision, mean Average Precision, Detection Speed, and Loss Function are selected as evaluation indexes in this experiment. The specific formulas are as follows:

$$P = Precision = \frac{TP}{TP + FP} \tag{1}$$

$$R = Recall = \frac{TP}{TP + FN} \tag{2}$$

$$AP = \int_0^1 P(r)dr \tag{3}$$

$$mAP = \frac{\sum_{i=1}^k AP(i)}{C} \tag{4}$$

Precision is a measure of how accurately the model predicts defects in solar panels; Recall evaluates the comprehensiveness of the model detection; mAP is the mean value of defect precision for each category, and k represents the number of defect categories. TP is the number of positive classes predicted to be positive; FP is the number of negative classes predicted to be positive; TN is the number of negative classes predicted to be negative; and FN is the number of positive classes predicted to be negative.

4.3. Analysis of experimental results

The training and validation sets are fed into the network for iterative training and Table 4 shows the results:

Table 4. Comparison of experimental results

Model	Precision/%	Recall/%	mAP/%	Times/ms
Faster R-CNN	90.1	91.6	92.1	243.8
SSD	88.2	87.9	86.1	82.8
YOLOv3	89.4	87.0	87.4	12.1
YOLOv5	85.7	84.5	86.9	12.8
YOLOv7	84.6	83.8	85.2	24.0
YOLOv8	86.3	87.8	89.1	10.6

As can be seen from Table 4, all six target detection algorithms achieve good detection results. Faster R-CNN performs the best in Precision, Recall and mAP, and mAP reaches 92.1%, which meets the precision requirements, but the computation is complicated, and the detection time is longer; SSD recall is excellent, and the detection time is still very large compared to the other one-stage algorithms. YOLO series model running time is faster, to meet the basic detection speed requirements, but the precision is slightly inferior to the Faster R-CNN, of which, YOLOv3 achieves higher detection precision, detection speed also has a very good performance. YOLOv7 all aspects of the performance is smaller than the other YOLO series algorithms. Due to its own lightweight network structure, YOLOv8 has the fastest detection speed, reaching 10.6ms, while Precision and Recall also perform better.
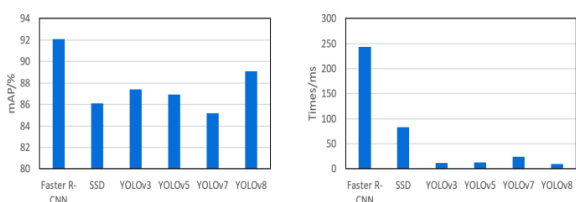
Figure 5. Performance Comparison of Algorithms

By comparing and analyzing Figure 5, we can see that the Faster R-CNN performs well in terms of accuracy, but has a slower processing speed of 243.8ms. In contrast, the YOLO series of one-stage algorithms have a clear advantage in processing speed. Among them, YOLOv8 has the fastest processing speed of 10.6ms and also has a high mAP value. This indicates that the YOLO series algorithms are more suitable for performing solar spot panel defect detection in real time.

Figure 6 shows the comparison of localization loss and classification loss function of YOLO series algorithm.
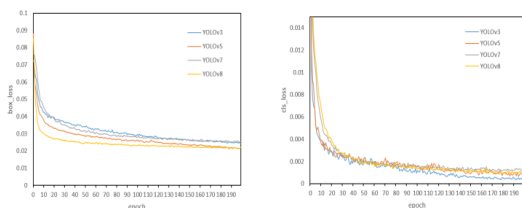

Figure 6. Comparison of localization loss function and classification loss function of YOLO series

As can be seen from the figure, all four types of algorithms in the YOLO series show good convergence ability. Among them, YOLOv8 algorithm has the best performance in the localization loss function, the speed of convergence in the early stage is faster, which represents the stronger learning ability of the algorithm, and the convergence curve of the algorithm is the smoothest, which indicates that the algorithm has better robustness. At the same time, the algorithm also has good performance in the classification loss function, YOLOv3 has the best performance in the classification loss function, but the performance in the localization loss function is relatively poor. Combining the performance of the two loss functions, the YOLOv8 algorithm shows a more comprehensive performance.

In summary, among the one-stage algorithms, the YOLOv8 algorithm has the highest precision rate, maintains good results in terms of recall and mAP values and has a smaller detection speed than the other algorithms. Meanwhile, YOLOv3 and YOLOv5 also have high precision and recall rates, and also maintain a faster processing

speed.SSD algorithm has a large gap in detection speed compared to other one-stage algorithms. Considering the actual production applications, the YOLOv8 algorithm is the most suitable algorithm model for solar panel defect detection in production line by combining both detection capability and detection speed.

5. Conclusion

This paper provides a comprehensive review of solar panel defect detection technology, mainly including fault types, fault causes and detection methods, summarizes the traditional defect detection methods of solar panels and the current mainstream deep learning detection methods, analyzes the principles and characteristics of different methods, and provides a reference for the research of solar panel defect detection. Six mainstream deep learning algorithms are compared and analyzed experimentally, and the YOLO series of algorithms all show excellent performance through the comparative analysis of multiple evaluation indexes. Among them, YOLOv8 has the highest accuracy rate, has a high detection accuracy for a variety of defects while also having a faster detection speed to ensure real-time, to meet the demand for real-time monitoring on the production line, as the most suitable algorithm model for solar panel defect detection in the production line.

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