Advances in Artificial Intelligence, Big Data and Algorithms G. Grigoras and P. Lorenz (Eds.) © 2023 The Authors. This article is published online with Open Access by IOS Press and distributed under the terms of the Creative Commons Attribution Non-Commercial License 4.0 (CC BY-NC 4.0). doi:10.3233/FAIA230791

Intelligent Inspection Method for Photovoltaic Modules Based on Image Processing and Deep Learning

Tengda LI^a, Min HUA^{b,1} and Qin LI^c

^a Department of Industrial Energy Products, China Mobile (Shanghai) ICT Co. Ltd,

China

^b USC-SJTU Institute of Cultural and Creative Industry, Shanghai Jiao Tong University, China

^c Paint-shop engineer, Tianjin Branch of FAW-VW, China

Abstract. The photovoltaic industry is a key strategic initiative in achieving carbon neutrality and emission peak and receives national support as a sunrise industry. The solar cell module is the central part of a solar power generation system, and its production quality and cost have a direct impact on the overall quality and cost of the system. The EL quality inspection is crucial for ensuring the quality of PV modules. However, traditional methods of EL quality inspection, such as manual inspection or machine vision inspection, are found to be inefficient, prone to false detections, and expensive in terms of labour costs. Additionally, these methods may lead to secondary damage to PV modules due to human intervention during the inspection process. Therefore, this paper proposes an intelligent inspection method for PV modules based on image processing and deep learning to improve the efficiency and accuracy of EL QC. The method pre-segments module images using EL image data acquisition and pre-classifies module types based on a priori defect types and then performs secondary detection of defective types of PV module defects using Faster RCNN. The proposed method's effectiveness was verified by the EL images collected from an actual PV module production line. The algorithm model was able to label over 12 common defects with strong reliability and achieve a detection accuracy of over 98%. This greatly improves the efficiency and accuracy of EL detection of PV modules and reduces labour costs while improving the quality of PV module detection.

Keywords. Image processing, Defect classification, Deep learning, Faster RCNN

1. Introduction

With the rapid development of modern technology and industrial production, the energy consumed by human activities is increasing, and in today's shortage of oil, coal and other energy, the development and recycling of solar energy, wind power and other renewable energy is particularly important, solar energy as a green and clean energy, has become an important part of the current energy structure. A photovoltaic module is the core device of photovoltaic power generation, its production process will inevitably produce defective products, and such component defects will seriously affect the efficiency of

48

¹ Corresponding Author, Min HUA, Shanghai Jiao Tong University, China, Email: huamin@sjtu.edu.cn

power generation. To ensure the quality of photovoltaic module products, detection of PV module production, and installation process is difficult to detect subtle defects, such as cracks, broken pieces, false welding, short circuit, and so on, photovoltaic module manufacturers usually use electroluminescence (EL) technology, the principle of the injection of excess carriers into the crystalline silicon solar cells, carriers directly compound will radiate infrared light, infrared light detector received to form an image, at the cell defects The luminescence is relatively weak, you can judge the defects of the battery according to the luminescence brightness, and the defective panel will be reworked appropriately according to the defect type.

In traditional PV module production, the defect detection of EL images is usually performed by manual visual inspection method, however, the traditional manual visual inspection method has the disadvantages of high labour cost, poor accuracy, low efficiency, and secondary damage to the product caused by manual operation, which is no longer suitable for the current automated production environment.

How to quickly, accurately and automatically identify various types of defects in PV modules has become an important issue in the field of EL inspection of PV modules.

Many scholars have studied intelligent detection methods for PV modules. Mahmoud Dhimish [1] studied the frequency information of EL images after discrete Fourier transforms for detecting the internal minor defects in PV cells for minor crack defects in PV cells. The detection method can detect a single type of defect and is not suitable for the online detection of defects in PV modules. Kitiyanan [2] analyzed the relationship between the diffusion length of minority carriers and more colourful luminescence intensity during EL detection of PV cells and detected defects in PV cells by image processing. Li [3] used a mathematical morphological filtering process to achieve scratch detection by removing the background subgrid from EL images and then performing defect localization and area solution, and their experimental results showed that this method can effectively detect scratches in PV cells and calculate the defect area. However, this method can only detect scratch defects and is not well-compatible with other defects on PV panels. Wen Sun [4] conducted the detection of defects that may occur in the cell cutting and screen printing stages of PV cells. The preprocessing operations such as image filtering, top-hat transformation, edge detection, and morphological transformation were mainly performed, and the defects of missing corners and chipped edges were detected using the linear algorithm TSAP and the differential shadow method. The detection method has high accuracy, but it is mostly applicable to the chipped corners and chipped edges generated in the cell cutting stage and the grayscale and texture defects generated in the printing stage, and is not suitable for the defects such as dummy weld, over weld and star crack caused by the string welding of PV cell modules. Dou [5] studied the online detection of solar cell module defects based on EL images, completed the design and construction of an online solar cell module detection system based on the EL principle, and segmented the cell cells using image technology processing for the acquired EL images. The system image segmentation aspect based on the accurate resolution of segmentation points is not specifically studied by the authors, and the defect detection of this system still requires manual participation, and the effectiveness and generality of the detection algorithm need to be improved. Zhang [6] studied EL testing by processing silicon wafers from the same resistivity into cells and corresponding modules and found that mixed lamination of solar cells with different resistivities also affects the module luminescence, leading to uneven EL light

and dark. Deitsch [7] proposed a robust automatic segmentation method for electroluminescence (EL) images of photovoltaic modules, which is mainly For EL images with large distortions, the linear features of the bus bar and sink bar of the PV cell itself are used for segmentation. Then, the defect classification based on vector machine and the defect detection using end-to-end deep convolutional neural network (CNN) is studied for the segmented PV cells [8], which can detect defects for each PV cell in the PV module, but this detection method can only determine the probability of each cell having a defect and the probability of each cell having a defect. Akram [9] proposed a new method for defect detection in electroluminescent images of PV modules. This method is using a lightweight convolutional neural network (Light CNN) to identify defects in EL images, which has the advantages of strong computational power, fast realtime speed, and high detection accuracy. However, this scholar only determines whether a PV cell has a defect or not, and does not discuss different specific defect types. Deng [10] proposed a method to detect PV cell defects by fusing EL detection and electrothermal (ET) detection data and established a defect detection model for PV cell arrays using a combination of traditional image processing and deep learning based on the data set related to EL detection images of PV cells, and completed the detection of many common defects in PV cells by The defect category identification and localization as well as the evaluation of PV cell module grade are completed.

In general, various intelligent detection methods and deep learning methods have been applied to the field of EL inspection of PV modules and have achieved good results, but there are certain limitations and shortcomings in terms of defect types, defect category identification, and judgment accuracy. Therefore, based on the research of various scholars, this paper proposes an intelligent detection method for PV modules based on image processing and deep learning and performs defective PV module defects based on Faster RCNN type based on Faster RCNN for secondary detection. In this paper, the method is applied to a PV module manufacturer in Hebei province to achieve accurate identification and classification of EL quality inspection defects, replacing the original manual visual inspection method, and verifying the feasibility and effectiveness of the proposed method.

2. PV Modules EL Intelligent Detection Method

2.1. EL image Data Acquisition

The traditional EL image data is collected and saved locally by the device and transmitted to the edge computing server through the wired network, which is limited by the shortcomings of industrial site network quality and small bandwidth, and the real-time data transmission is difficult to be guaranteed.

In this paper, EL image data acquisition and transmission method based on a 5G smart gateway is used to collect data from production sites through the 5G smart gateway and upload data scattered in many devices and systems in production sites to edge computing services with the characteristics of large bandwidth, wide connectivity and low latency of 5G private network. The EL image data acquisition and transmission process is shown in Fig.1.

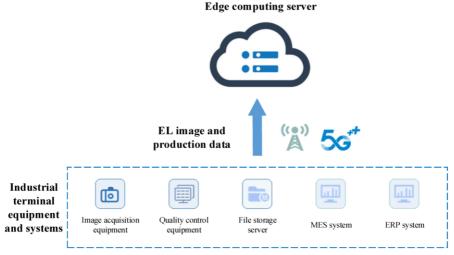


Figure 1. Example of a figure caption.

2.2. EL Image Processing

The EL images of PV modules are usually of high resolution, and the whole EL image is often large and contains several single cells (as shown in Fig.2), the small defective part of a single cell is very small compared to the whole EL image, and the defect detection directly on a very large size image is prone to defect leakage and misdetection, and the detection accuracy and robustness are not high.

The EL images of PV modules are usually of high resolution, and the whole EL image is often large and contains several single cells (as shown in Fig.2), the small defective part of a single cell is very small compared to the whole EL image, and the defect detection directly on a very large size image is prone to defect leakage and misdetection, and the detection accuracy and robustness are not high.

To improve the accuracy and robustness of the whole EL image detection, it is necessary to process the EL image first. In this paper, we propose a pre-segmentation method for EL images of PV modules to divide the EL image and get the image of the region where each single cell is located.

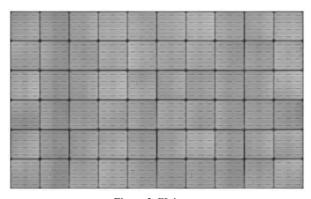


Figure 2. EL image

2.3. Component Type Pre-Classification

To improve the efficiency of PV module detection and reduce the consumption of computational resources, this paper pre-classifies individual PV cells as normal or suspected abnormal.

The steps for pre-classification are as follows:

STEP1: count the average brightness of the image in the area where each single cell is located, if the average brightness is lower than 50, the single cell is judged to be a short-circuit defect;

STEP2: Create a single-cell template with a positive sample, and compare the single-cell with the single-cell template after excluding short circuit defects, if the similarity is higher than 80%, it will be judged as a positive sample without defects, and vice versa as a candidate negative sample.

2.4. Secondary Defect Detection Based on the Faster RCNN Model

1) Defect classification and sample training

Analyze dozens of defect types of PV module EL, including forked hidden cracks, linear hidden cracks, dendritic hidden cracks, broken grids, broken pieces, mixed files, black spots, black pieces, black edges, line marks, dummy soldering, over-soldering, and so on.

The four types of defects, forked hidden cracks, black spots, black flakes, and line marks, are shown in Fig.3-6, and the other types of defects are not listed.

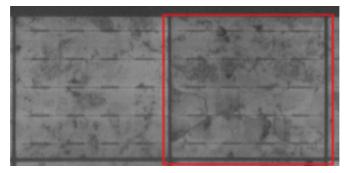


Figure 3. Forked cryptorchidism

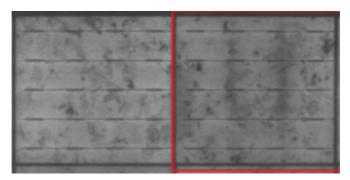


Figure 4. Black spot

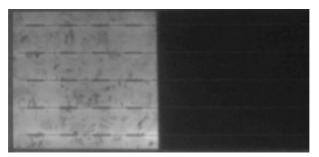


Figure 5. Black film

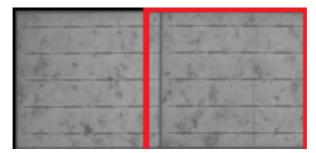


Figure 6. Line marks

Defect type samples are trained as UnitImage of each defect, using LabelImg for defect type and location labelling, including the 12 types of defects mentioned earlier, and the labelling information is saved as xml files, with 200 groups of each defect type labelled.

2) Faster RCNN model

Faster RCNN integrates feature extraction, proposal extraction, bounding box regression (rect refine), and classification in one network, which makes the comprehensive performance improve. The schematic diagram is shown in Fig.7.

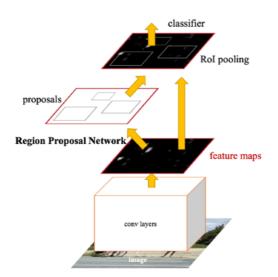


Figure 7. Diagram of Faster RCNN

As shown in Fig.8, the Faster RCNN detection model used in this paper consists of four main modules, which are conv layers, RPN (Region Proposal Network), RoI pooling, and classification & regression.

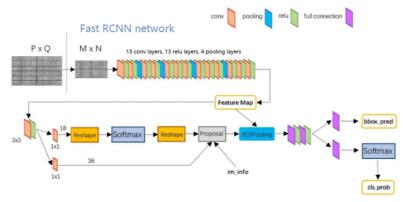


Figure 8. Detail structure of Faster RCNN

3) Secondary defect detection

The secondary defect detection uses the Faster RCNN mentioned in the previous section to detect the PV panels suspected to be abnormal after pre-classification to further clarify their specific defect types, and the main steps are as follows:

STEP1: divide the target detection labelled data set into a training set and test set, make normalization, scale image pre-processing, make the image conform to the network structure and reduce the requirement for computational resources, then set the input image parameters such as width, height, type and initial weight file, train the model until convergence, or reach the set number of epochs, save the weight file;

STEP2: Load the trained Faster RCNN model weight file and perform defect detection on the current UnitImage.

3. Experimental Results and Analysis

To verify the feasibility and effectiveness of the method proposed in this paper, the authors' team built a 5G-AI quality inspection platform, which consists of a software platform and algorithm services, and the Faster RCNN model is combined with CV vision algorithms to achieve intelligent inspection of EL images of PV modules.

The 5G-AI quality inspection platform architecture is shown in Fig.9.



Figure 9. 5G-AI quality inspection platform

This paper adopts the production data of a PV module manufacturer in Hebei province for testing (the testing software is shown in Fig.10), and can label more than 12 common defects, with detection accuracy greater than 98%, false detection rate reduced by 10%, product defect leakage rate less than 0.2%, which fully proves the feasibility and effectiveness of the method proposed in this paper.

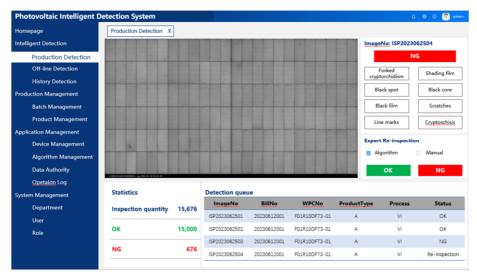


Figure 10. Test software running chart

4. Conclusion

This paper presents a novel approach for detecting defects in PV modules using image processing and deep learning. The method involves pre-segmenting the module images and pre-classifying the module types according to the a priori defect types. The defective types of PV module defects are detected twice using Faster RCNN. The proposed method's effectiveness and superiority have been verified through the actual operation data of enterprises. This method can be applied to other vision inspection fields, such as PCB welding quality inspection and vehicle body scratch detection. which is of great significance to the exploration of intelligent inspection technology based on machine vision.

References

- Mahmoud Dhimish V H. Solar cells micro crack detection technique using state-of-the-art electroluminescence imaging. Journal of Science: Advanced Materials and Devices, 2019, 4: 499-508
- [2] Fuyuki T, Kitiyanan A. Photographic diagnosis of crystalline silicon solar cells utilizing electroluminescence. Applied Physics A, 2009, 96(1): 189-196
- [3] Li Yajuan, Huang Wei, Zhou Xiang. Research on the scratch detection method of solar panel based on mathematical morphology. Electromechanical Technology, 2016, (1): 16-29
- [4] Sun Wen. Research on the detection of defects in solar panels. Master thesis, Huabei Normal University, 2017

- [5] Dou Jingbao. Online inspection of solar cell module defects based on EL images. Master thesis, Zhejiang University of Technology, 2013
- [6] Zhang ZM, Liu Miao, Xu ZW, et al. Study of EL light-dark unevenness in PERC monocrystalline PV modules. Solar Energy, 2019, 9: 36
- [7] Deitsch S, Buerhop-Lutz C, Maier A, et al. Segmentation of Photovoltaic Module Cells in Electroluminescence Images. arXiv preprint arXiv. 1806.06530v3: 1-22
- [8] Deitsch S, Christlein V, Berger S, et al. Automatic classification of defective photovoltaic module cells in electroluminescence images. Solar Energy, 2019, 185: 455-468
- [9] Akram M W, Li G, Jin Y, et al. CNN based automatic detection of photovoltaic cell defects in electroluminescence images. Energy, 2019, 189: 116319
- [10] Baoyuan Deng, Yunze He, et al. The art of writing a scientific article. Journal of Mechanical Engineering, 2021, 57(08): 98–106.