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Solar Panel Defect Detection Based on Convolution Neural Network

Electric Power System Engineering

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1. Introduction

Nowadays photovoltaic power generation has become one of the important sources of electricity in our life. Because solar panels are expensive and difficult to move in size and weight, fault detection and repair of solar panels need to be more rapid and accurate. Electroluminescence (EL) imaging is a useful modality for the inspection of photovoltaic (PV) modules. With its high resolution, EL images can detect the surface of solar panels and their tiny defects. However, because manual analysis of EL images requires much expertise on defect, defect analysis is often a lengthy and expensive process.

In this paper, we use the convolutional neural network (CNN) running on Graphics Processing Unit (GPU) to automatically classify EL images, so as to detect defects of cells on each solar panel. In this work we analyzed 2,664 cells from the solar panel, (Fig.1) [1]-[3] dividing them into 2,100 training data and 564 test data and classifying them into four types according to the degree of defect. In the process of building convolution kernel, we use ResNet to build a deeper network and analyze more defect characteristics. At the same time, the system is normalized to reduce the error and improve the accuracy. The results of type analysis and accuracy of single EL image and multiple EL images are satisfactory. In the overall test, the accuracy of class 1 defects reaches 91.03%, which proves that this method is effective and feasible in automatic analysis of solar panel defects.

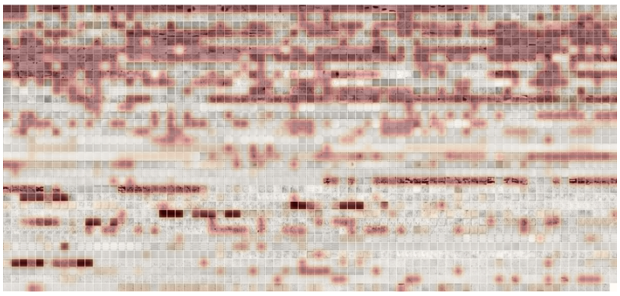

Fig.1 2664 photovoltaic cell image samples

Defection analysis

Solar panels are often protected from rain, wind, and snow by aluminum frames or glass panels, but this does not provide good protection from other damages. Falling branches, hail, installation errors and other factors can cause damage to solar panels. These defects can be visible to the naked eye, or even to experts, but these small defects could also reduce the efficiency of solar panels in the future. As shown in Figure 2 and 3, [1]-[3] general defects are divided into two categories, one is the damage caused by the passage of time defects (Fig.2), and the other one is due to the material or processing caused by the inherent defects (Fig.3). We combine the high resolution generated by the current characteristics of EL images with the automatic and high precision characteristics of mechanical learning to analyze all kinds of visible defects or minor defects of solar power panels.

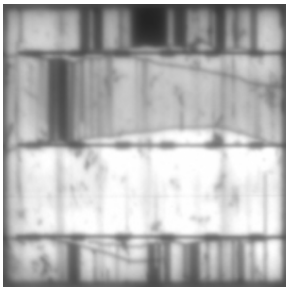

Fig.2 Obvious defect

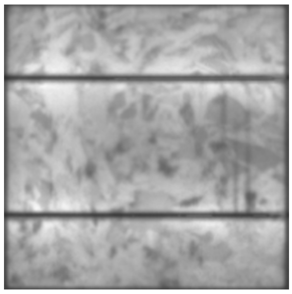

Fig.3 Microcrack

3. Methodology

3.1 Data classification

We chose the Python language and used Pycharm as the tool to run the language. Pycharm is a Python Integrated Development Environment (IDE) that helps improve the efficiency in Python Development. Then, we used high-resolution EL images of 2624 aligned solar panel cells as a dataset and labeled them. We divided the images into 4 types according to the labels based on whether defects had been self-evaluated: (1) The judgment was defective and consistent with the self-assessment. (2) The judgment was functional and consistent with the self-assessment. (3) The judgment was functional but not self-confident with the self-assessment. (4) The judgment was defective but not self-confident with the self-assessment. Then we classified the four defect degrees into 1, 0, 0.33%, and 0.67 according to the self-assessment weight.

3.2 Build model

We use the ResNet [4] architecture because it allows us to build deeper networks and help us get more sample features. Accordingly, because the deep network data loss errors are many, we need to normalize the program. We resize and input the appropriate tensor compatible to the resolution of our solar cell image samples (300 × 300 × 3), in order to avoid additional down sampling of the samples. At each layer of the algorithm, we constructed two convolution layers according to input and output channels, convolution kernel size, convolution step size, padding size, bias or not, and created four residual groups of 3,4,6, and 3 respectively after batch normalization.

3.3 Data analysis

In order to bring up images at the same time, we converted the image format to RGB, scaled the resolution of the test set to 256 multiplied by 256, clipped the center to 224 multiplied by 224, transformed it to tensor format, adjusted the normalized mean and standard deviation. In this way, we can get the defect types and accuracy of individual images and observe the images at the same time, as shown in Figure 4.

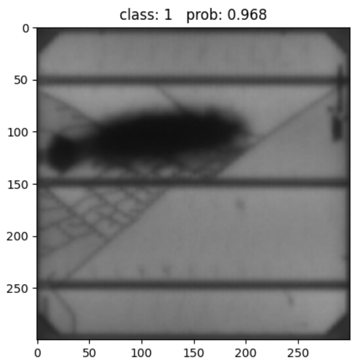

Fig.4 Defect type and accuracy of single image

3.4 Overall training and test results

In the experiment, we divided a total of 2664 pictures into 2100 training data samples, and the remaining 564 pictures were used as test samples. The algorithm was used to analyze all types of defective cells, as shown in Table 1. Results of training data of class 1 (weight 1) and class 2 (weight 0) were as accurate as 94.02% and 81.12%, respectively. However, due to the small number of samples of class 3 (weight 0.33) and class 4 (weight 0.67), the computer cannot accurately learn the characteristics of these defect types, which cannot reach the expectation. In this case, and with a smaller test data set, we ignored defect class 3 and 4 in our tests. But because of the same problem, the accuracy of defect class 2 (weight 0) is also reduced.

Table.1 Experimental results

Train	Class 1	Class 2	Class 3	Class 4
Accuracy	94.02%	81.12%	25.42%	9.52%
Test	Class 1	Class 2	Class 3	Class 4
Accuracy	91.03%	59.44%	0%	0%

4. Conclusion and future work

Due to the high accuracy of defect class 1, we believe that the method of automatic defect detection by CNN is feasible, but the experimental method still needs to be improved. The reason for the inaccurate results of other defect types is that the data set is too small, so the next major step is to expand the data set. We considered expanding the number of samples by rotating images and mirroring, and making the data volume of the four defects consistent, so as to better compare the test results.

5. References

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