Automatic Detection of Photovoltaic Module Cells using Multi-Channel Convolutional Neural Network

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***Abstract*—Due to the complexity production of photovoltaic (PV) module cells, it is easy to generate defects such as broken grid, open weld and hidden crack in many processes. Based on artificial feature extraction method is time-consuming, low recognition rate, the traditional convolutional neural network (CNN) relys on a single channel to extract image feature is not sufficient, this paper proposes a method of multi-channel convolutional neural network(MCCNN) to detect the defects in PV module cells, multi-channel has the scale of different image size, it is able to extract the image feature from different scale, The features are fused on the fully connected layer, finally through the Random Forest(RF) classifier to classify, it can improve the accuracy of recognition. Simulation results show that the MCCNN can quickly and accurately identify the PV module cells defect and defect categories, and accurately mark it on the original image.**

Keywords—photovoltaic module cells, defect recognition, multi-channel convolutional neural network, random forest classifier

I. INTRODUCTION

Solar energy is a sustainable natural energy. In factories, Due to artificial factors, Photovoltaic (PV) modules are easy to generate broken grid , open welding, solid black, shadow and hidden crack defects, it will seriously reduce the photo electric conversion rate and life of PV modules[1-3]. In recent years, with the rapid development of infrared (IR) technology and machine vision, the performance of visual inspection technology has been greatly improved. Automatic visual inspection technology has gradually replaced traditional manual detection [4-5]. Gong et al. [6] proposed a surface defect detection method based on independent component analysis (ICA) . Zhang et al. [7] proposed the combination of bimodal method and otsu method in defects detection in Solar Cells. Zhang et al. [8] proposed a visual inspection method for silicon solar cells . In addition, M Du and A Bastari used anisotropic diffusion method, texture analysis method to detect surface crack defects of solar cells [9-10]. The traditional defect classification algorithm is based on feature extraction from defect regions.Traditional defect detection and classification algorithms have poor adaptability, and usually need to be redesigned for specific problems. In recent years, the convolutional neural network (CNN) has been used successfully in many fields. such as image recognition[11-12]and natural language processing [13-14]. Due to its powerful feature learning ability, CNN can learn appropriate features for different problems and has a very strong adaptability. Therefore, this paper propose a multi-channel convolutional neural network (MCCNN) to detect the defects of PV modules. Experiments show that this method can identify the defects of PV modules with 96.76% accuracy and label the defects on the small solar cells.

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II. IMAGE PREPROCESSING

A. Image preprocessing of Photovoltaic Module Cells

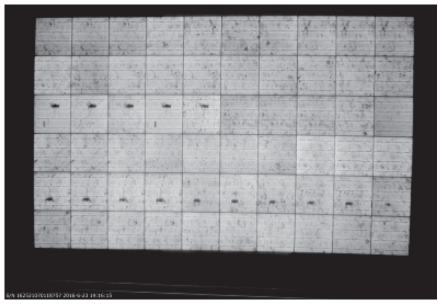

Fig.1 EL image of the assembled PV Module Cell

An EL image of an assembled PV module cell contains 60 small solar cells as shown in Fig. 1. the original image has black background, image tilt, perspective issues. The original image of the PV module is not easy to be directly used for CNN recognition, it needs to do appropriate pre-processing work, The processing steps as shown in Fig. 2.

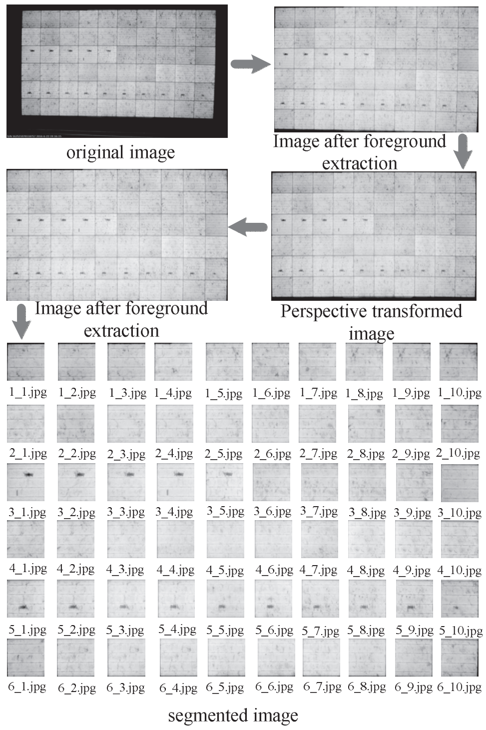

Fig.2 Small solar cells extraction process

B. Various defects in PV Module Cells

Common defects of solar cells include solid black, broken grid , hidden crack , shadow, open welding and so on.

The defects are located inside the small square panels, as shown in Fig. 3.

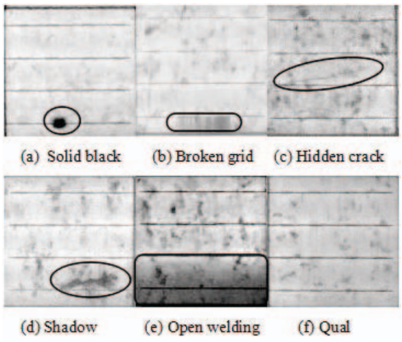

Fig.3 Various defects in solar cells

we can see the characteristics of each type of defect in Fig. 3. (a) solid black: This type defect appears as dark solid black spots, mainly at the edge and corner of the solar cell. (b) broken grid: This type defect appear as vertical dark stripe. (c) hidden crack: This type defect appears as a crack with unfixed position and length. (d) shadow: This type defect appears as a darker color with a distinct shadow compared to the background. (e) open welding: This type defect appears as a uniform dark shadow parallel to the electrode line and appears at the bottom of the solar cell.

C. *Data set*

In order to verify the validity of the algorithm, Firstly construct an image database for defect recognition of solar cells. Secondly the data set is divided into "qual-defect" two-class data set and "multi-defect" five-class data set. The two-class data set contains qual samples and defect samples. The five-class data set contains five kinds of defects, respectively are solid black, broken grid, hidden crack, shadow and open welding .

D. *CNN model*

In this paper, we use two MCCNN models for PV modules defect detection and classification. The process of identify defect is shown in Fig. 4.

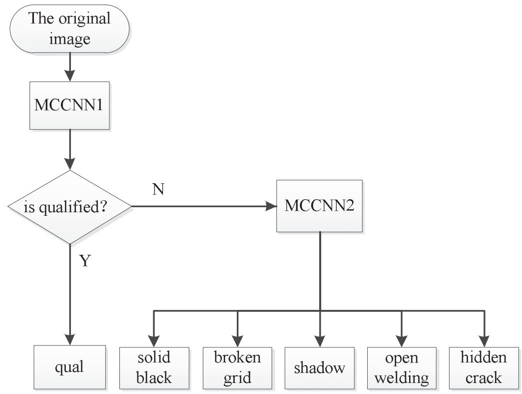

Fig.4 Defect recognition process

Firstly, use MCCNN1 model to distinguish whether an EL image of an assembled PV module cell is qualified or not, if not qualified, Then use MCCNN2 model to identify which of the five categories of defects belong to.

III. MULTI-CHANNEL CONVOLUTIONAL NEURAL NETWORK

A. *convolution neural network*

CNN is a kind of data structure specially used to deal with similar grid structure. CNN is composed of input layer, convolution layer, pooling layer, fully connected layer and output layer. The traditional CNN is a single channel network, In the "qual-defect" recognition of solar cells, the single-channel CNN recognition model is shown in Fig. 5.

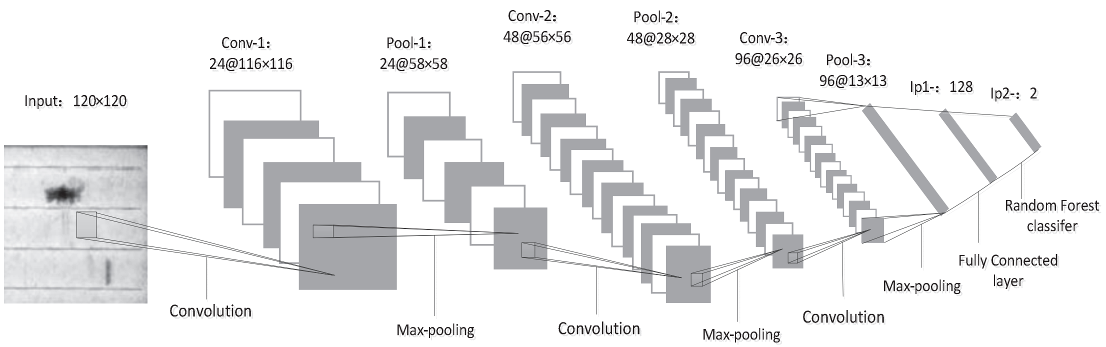

Fig.5 CNN_{120} model structure diagram

Convolution operation helps to improve machine learning system through three important ideas. sparse interaction, parameter sharing and pooling. Sparse interaction means that the neural unit of a layer of network only connects with a part of the input unit from the network of the previous layer, instead of creating a connection between each layer between the layers as in the traditional fully connected neural network. Parameter sharing means that multiple functions in the model use the same parameters, this means that features in a certain part of the image can be applied to other parts of the image. Through sparse interaction and parameter sharing , the goal of greatly reducing the number of connection parameters in the network is achieved. Pooling is also known as subsampling, which compresses the image, reduces the size of the image to reduce the number of parameters. It can help model to avoid overfitting and obtain local translation invariance. The structural parameters of the CNN_{120} model is shown in Table1.

TABLE I. CNN_{120} MODEL PARAMETERS

Layer	Type	Kernel size	Kernel numbers	Stride
1	Convolutional	5*5	24	1
2	Max pooling	2*2	24	2
3	Convolutional	3*3	48	1
4	Max pooling	2*2	48	2
5	Convolutional	3*3	96	1
4	Max pooling	2*2	96	2
9	Fully connected	128		

B. *Multichannel convolution neural network model*

The traditional CNN has only one channel, The feature of single-channel CNN extraction is not sufficient. Therefore, this paper uses a MCCNN to extract more features from images, considering the size of the solar cells and the structure of the network, we use the image size of the solar cells are 30×30, 60×60, 120×120, and use CNN to extract image features of different scales. according to the size of the image different scales, we named the CNN model as CNN_{30} , CNN_{60} , CNN_{120} . The structure of the MCCNN1 model is shown in Fig. 6.

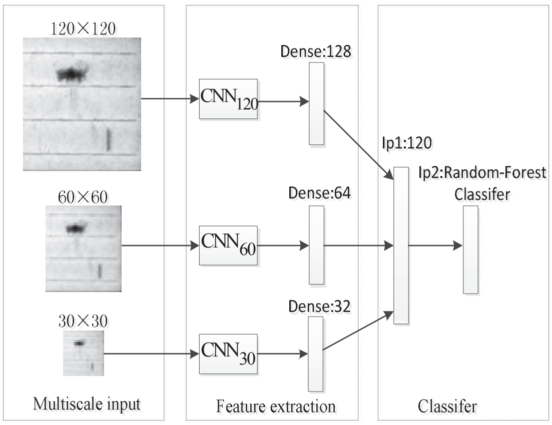

Fig.6 Architecture of MCCNN1

C. *CNN architecture of each scale*

In the experiment of defect identification of solar cells, the structure parameters of MCCNN1 are shown in Table 2.

TABLE II. MCCNN1 ARCHITECTURE

Layer	CNN_{30}	CNN_{60}	CNN_{120}
Conv-1	3×3 24	5×5 24	5×5 24
Pool-1	2×2 24	2×2 24	2×2 24
Conv-2		3×3 48	3×3 48
Pool-2		2×2 48	2×2 48
Conv-3			3×3 96
Pool-3			2×2 96
Ip1	32	64	128
Ip2	2	2	2

Fig. 6 is the structural diagram of the MCCNN1 model. It consists of three models. The image features extracted from multi-channel are fused to the full connection layer for training. and finally output by the Random Forest classifier. Table 2 is the parameters of the three models . The left side of the table indicates the size of the convolution kernel, and the right side are the number of convolution kernels.

D. *Experimental evaluation*

F-Measure is a commonly used comprehensive indicator for evaluating and comparing network performance. F-Measure is the weighted harmonic averaging of Precision and Recall, which can be used to measure the performance of the classification method and determine whether a classification model is good or bad. The formulas are as follows:

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F\text{ - }measure = \frac{2 * Recall * Precision}{Precision + Recall} \quad (3)$$

TP represents a positive example sample correctly classified by the classifier, FP represents a negative example sample that is incorrectly marked as positive example data, and FN represents a positive example sample that is incorrectly marked as negative example data.

In order to verify the performance of CNN on the dataset at different scales in multiple channels on the established “ qual-defect” data set, we use CNN_{30} model , CNN_{60} model, CNN_{120} model and the combination of the two models do experiments compared with MCCNN1. This experiment is implemented on the keras environment built under the windows system. On the established "qual-defect" data set, 60% of the data were randomly selected from the train set and test set for training and 40% for testing, The comparison results are shown in Table 3.

TABLE III. DIFFERENT MODEL PERFORMANCE ON DATA SET

Method	Precision	Recall	F-measure
CNN_{30}	0.8380	0.8013	0.8192
CNN_{60}	0.8453	0.8084	0.8264
CNN_{120}	0.8654	0.8152	0.8396
CNN_{60} - CNN_{30}	0.9050	0.8210	0.8610
CNN_{120} - CNN_{30}	0.9189	0.8510	0.8836
CNN_{120} - CNN_{60}	0.9365	0.8821	0.9085
MCCNN1	0.9573	0.9046	0.9302

The experimental results are shown in Table 3. It can be seen from Table 3 that the MCCNN1 has the best performance in solar cells defect recognition, and the F1 value is 0.9302, higher recognition rate than single channel

CNN and two channels combined CNN. The new MCCNN structure proposed in this paper has obvious advantages compared with the traditional single-channel CNN structure. The MCCNN1 structure can effectively extract the advanced features of the hierarchical structure. Traditional CNN is a single channel and one scale to extract image feature is not sufficient. MCCNN has strong robustness in multi-channel and different scales. MCCNN can significantly improve the learning ability of features and overcome the limitations of traditional feature extraction.

E. Random Forest Classfication

The Random Forest algorithm is a combination algorithm based on classification and regression decision tree proposed by Breiman et al. [15]. This paper uses the random forest classifier as the last layer of MCCNN. The construction of the random forest model is generated by the following three steps:

Step1: Obtain the training data set, assuming that there are N samples in the training set, and randomly extract K samples by using the sampling method with the return, so that K training subsets $\{D_1, D_2, ..., D_k\}$ are obtained.

Step2: Using the training subset D_i, (1 ≤i ≤K) to construct the sub-decision tree, assuming that the number of sample features is M, and selecting F samples from M to form a random feature subspace X_i as the split attribute set of the current node of the decision tree. The decision tree is established to obtain the best segmentation point, and the optimal splitting attribute is selected from the random feature subspace X_i to split the node.

Step3: Every tree will grow completely without pruning. Each decision tree outputs one result, and then counts the voting results of the decision tree. The output of the random forest gets the most votes.

In the process of solar cells defect identification, The background of the picture is more complicated, Use CNN-RF model can improve the generalization ability of the network and improve the recognition accuracy. In order to verify the performance of different classifiers on the data set, we use svm classifier, random forest classifier and knn classifer do experiment. Table 4 shows the parameters of classifers.

TABLE IV. THE PARAMETERS OF CLASSIFERS

Classifer name	Parameter name	Parameter value
KNN	n_neighbors	3
	leaf_size	30
	algorithm	auto
SVM	c value	1
	kernel function	rbf
RF	n_estimators	10
	max_depth	5
	max_features	1
CNN	epoch	30
	activation	relu
	optimizer	adam

F. Experimental evaluation

We use the MCCNN2 combined knn classifier, svm classifier ,random forest classifer do experiment , MCCNN2 was implemented using Keras environment and Scikit-learn packages. 4167 samples were selected for training and 2778 samples were used as test, Fig 7 shows the confusion matrix of five-class solar cells detection classification.

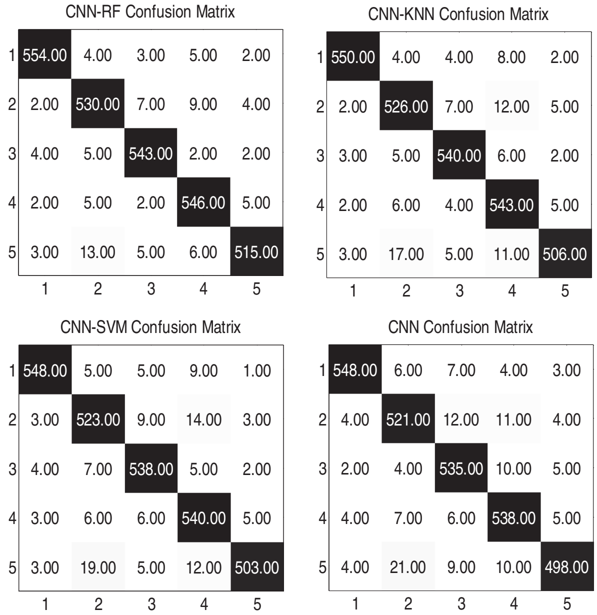

Fig. 7. The confusion matrix of MCCNN2 combined classifers

As can be seen from the Fig.7, the random forest classifier accuracy and recall rate are higher than other classifiers, and the recognition of the solar cells defects are the best. Due to random forest is an important bagging-based ensemble learning method, which combines multiple weak learners to form strong learners. It is composed of many decision trees, and uses multiple classification trees to discriminate and classify data. It has a very high accuracy. due to the randomization of data and the randomization of the features to be selected, it can avoid the phenomenon of over-fitting and improve the diversity of the system, thus improving the classification performance. Compared with other classifiers, the random forest classifier has easier implementation and better performance in data sets.

IV. EXPERIMENT AND ANALYSIS OF RESULTS

A. MCCNN parameter sets

In this paper, the method of Mini-Batch Gradient Descent is adopted in the training of the model. Each training is based on a certain batch size .The MCCNN-RF model sets the batch size to 25, Dropout to 0.5, MCCNN-RF model use the Adam optimizer train network . Its hyperparameter selection reference [16] is set to lr=0.001, beta1=0.9, beta2=0.999, epsilon=1e-08, where lr is the learning rate, beta1 and beta2 are numbers between 0 and 1, and epsilon is a fraction greater than zero that is set to prevent division by zero.

B. "Qual-defect" Recognition results

This experiment is implemented on the keras environment under the windows system. On the established "qual-defect" data set, according to the selection of the parameters and the establishment of the multi-channel CNN model, 60% of the data were randomly selected from the train set and test set for training and 40% for testing. the sample size of the "qual-defect" two-category data set is shown in Table 5. After 30 iterations, the test set achieved an accuracy of 96.78% on a MCCNN network.

TABLE V. "QUAL - DEFECT" TWO CLASSIFICATION RESULTS

Type	Train set	Test set	Accuracy	Misclassification
qual	4134	2756	96.81%	88
defect	4167	2778	96.76%	90
total	8301	5534	96.78%	178

C. "Five classification defect recognition results

The number of samples of the multi-defect five-category data set is shown in Table 5. 60% of the data were randomly selected from the train set and test set for training and 40% for testing. Experiment in the MCCNN2 model. After 30 rounds of iteration, the multi-defect five-category test set is on the multi-channel CNN network. It achieved an accuracy rate of 96.76%. The results are shown in Table 6:

TABLE VI. MULTI-DEFECT FIVE CLASSIFICATION RESULTS

Type	Train set	Test set	Accuracy	Misclassification
open weldding	852	568	97.54%	14
broken grid	828	552	96.01%	22
solid black	834	556	97.66%	13
shadow	840	560	97.50%	14
hidden crack	813	542	95.02%	27
total	4167	2778	96.76%	90

In order to verify the effectiveness of the proposed method, the method of [17] ICA and the method of [18] visual saliency were used for comparison test. The results are shown in Table 7.

TABLE VII. COMPARISON OF DEFECT RECOGNITION METHODS FOR SOLAR CELLS

Algorithm	Accuracy/%
Visual Saliency	86.7%
ICA	93.4%
MCCNN	96.76%

As shown in Table 7, Compared with ICA and Visual Saliency algorithms, MCCNN has the highest accuracy and the best effect. CNN can not only extract effective features from "big data", but also use some features of weight sharing and activation function Relu, which greatly improve the efficiency of defect recognition.

A PV module component image is first cut into 60 small solar cells. this solar cells identified by the MCCNN1 model, and the recognition result is displayed in a probabilistic manner. The small square area determined to be defective is represented by orange color, and then these defects are identified by the MCCNN2 model, and the defect type is probabilistic. Determining which type of defect belongs to, the defect category displayed by the highest probability is the final defect, the row name is a certain type of defect, and the column name is the location of the defect.The result of a panel defect identification is shown in the fig.8.

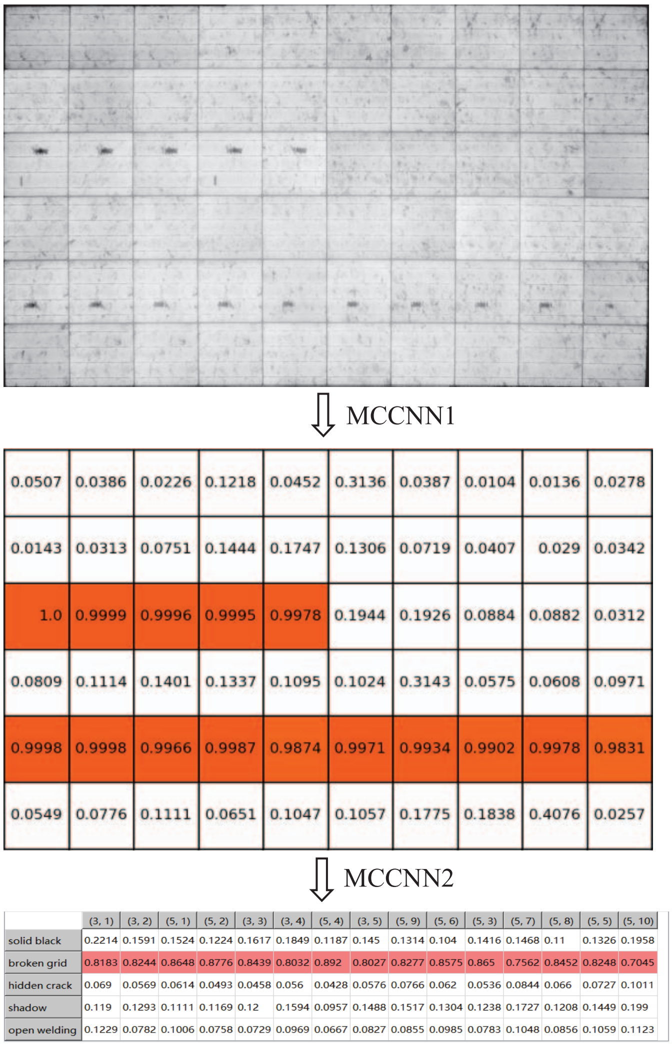

Fig.8 Defect probabilities inferred for each PV module cell by the proposed CNN, Red frame indicates the highest probability of a solar cell defect.

V. CONCLUSION

The production process of PV module cells are complicated, and the manual detection of defective images is time-consuming and laborious. Based on CNN model, this paper proposes a MCCNN method for detecting PV module cells defects, using Matlab, Python tool, completed the experimental design. The experiment shows that the combination of MCCNN and random forest classifier has achieved good results in the problem of PV module cell defect identification. Greatly improved the recognition rate of defects. In the research of PV module cells defects, CNN has great advantages and application prospects.

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