

A SURVEY ON DEEP LEARNING-BASED SOLAR CELL DEFECTS IDENTIFICATION AND CLASSIFICATION FROM ELECTROLUMINESCENCE IMAGING

C. Daxayani¹, Dr. N. P. Ananthamoorthy²

¹Research Scholar, Department of Electrical and Electronics Engineering, Hindusthan College of Engineering and Technology, Coimbatore, Tamil Nadu, India

²Professor & Head, Department of Electrical and Electronics Engineering, Hindusthan College of Engineering and Technology, Coimbatore, Tamil Nadu, India

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ABSTRACT

Renewable energy sources now play a significant part in addressing the growing energy demand for the protection of the environment. The fast-growing innovation in eco-sustainable power is solar energy, supplied by huge solar fields. But, its productivity degrades from solar cell flaws that arise during deployment or are induced by weather occurrences. The images of electroluminescence (EL) can make these faults obvious. The manual categorization of these EL pictures takes an incredible amount of cost and time and is sensitive to subjective changes in the inter-examiner. To combat this problem, many deep learning algorithms have been developed in the past few centuries to identify and categorize the solar cell defects or failures in the EL images. This paper gives a complete review of the solar cell defect classification from several imaging methods. First, the diverse deep learning classifiers using EL images for the identification and categorization of solar cell abnormalities discovered by current researchers are briefly explored. A comparison analysis is then carried out to analyze the difficulties in those classification models and suggests a new approach that improves the precise categorization of flaws in the solar cell from EL images.

Keywords: Renewable energy source, Solar cell, Electroluminescence imaging, Defect classification, Deep learning.

1. INTRODUCTION

The sustainable source of electricity requires renewable resources. Apart from wind and water, solar energy, which now supplies roughly 2% of global energy requirements, is one of the most essential technologies [1]. It is generated mostly by large solar arrays with power ratings of up to 1GW. The overall generated power is decreasing throughout their lifespan, especially due to flaws in the photovoltaic (PV) panels and their cells. Solar modules are normally shielded from weather factors including rainfall, wind and snow by an anodized aluminium and crystal overlay. But, such protection strategies cannot always avoid surface defects resulting from collapsing twigs, lightning, or high temperatures induced by the PV modulus decreasing in the installation stage [2-3]. Further, manufacturing faults like improper fabrication or connections can also cause the PV panels to be broken. The defects in PV cells are primarily split into micro-crack, break and finger-interruption [4]. The finger-interruption does not always reduce the power transmission. The micro-crack flaws can destroy the entire the PV production and possibly cause failure in the panel. The flaws in polycrystalline as well as monocrystalline PV cells are illustrated in Figure 1.

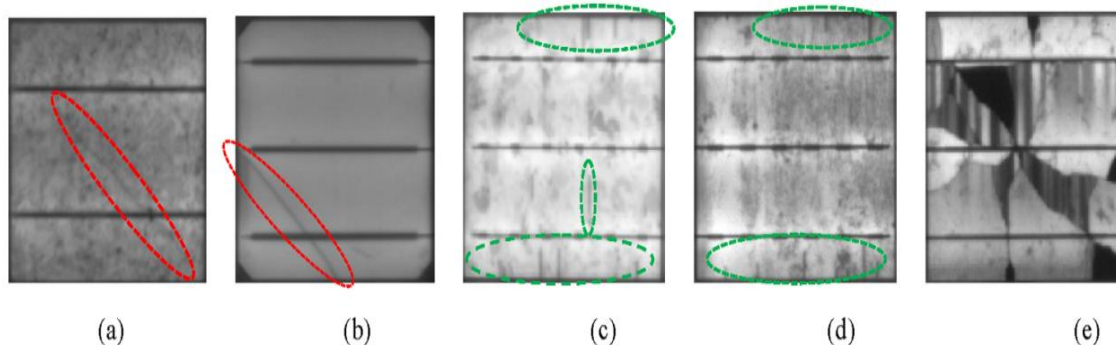


Figure 1: Various Categories of Flaws in Solar Cells. (a) Micro-crack in polycrystalline silicon, (b) Micro-crack in monocrystalline silicon, (c) Finger-interruption in monocrystalline silicon, (d) Finger-interruption in polycrystalline silicon, (e) Break.

The finger-interruptions, micro fractures and dislocated regions might develop during production because of the nonuniformity of silicon wafers. The cell disconnection, soldering failures and lamination faults might arise during the assembly process. All of these flaws have a distinct effect on the functioning of a PV module. Failures like cracked cells, cell disconnections and fractures might lower the power output of a whole module severely.

A growing range of natural disasters like rainfall and extreme temperatures make the analysis of solar panels and the detection of faults even more vital. Even for skilled professionals, it is very difficult to visually identify damaged components. Besides observable glass crashes, there are several deficiencies not noticeable to the eye, which diminish the effectiveness of a PV array. In contrast, observable faults do not always affect the efficiency of the system. The electrical characteristics of a panel should be determined accurately for the exact assessment of thermal efficiency. On the other hand, these measures demand manual interactions with specific diagnostic equipment and therefore do not extend well to huge solar power stations with thousands of photovoltaic modules. These assessments may also only represent one point in time and hence may not reveal some kinds of microscopic cracks that will be expected to become a concern over time [5-6].

The most important tests used to identify the faults for solar panels are I-V curve analysis, Infrared (IR) and EL imagery. I-V curve technique is based upon the measurement and graphic modelling of the output voltage and current of PV modules. Although a whole I-V curve may be used to identify the overall state of a complete module, the cell defect and the specific position of the faults cannot be determined. IR imaging provides a contactless, non-destructive alternative to direct solar modulus quality evaluations. The PV modules which are either partially or entirely cut off from the electrical circuit can easily identify solar cells that are damaged. The solar energy is therefore no longer transferred to electricity to heat the PV arrays. An IR camera can then view the emitted IR radiation [7]. On the other hand, the comparatively small resolution of IR cameras can limit the detection of minor faults, for example, microcracks, that still don't influence the photocatalyst performance of the PV arrays [8].

EL imaging is another well-known non-destroying method in the fault investigation of PV cells with a considerably greater resolution of solar panel images. Fault cells seem darker in EL pictures because the unconnected sections do not irradiate [9]. Using EL imaging, flaws such as cracks and inactive cell regions can be visualized for cell and PV array quality assessments. Analysis of these EL images manually takes time due to the great quantity of data. For this reason, many deep learning models such as Convolutional Neural Network (CNN), etc., have been developed which help to identify and categorize the faults in the solar cell images [10]. For automatic classification, various types of CNN structures were created, e.g. AlexNet and VGG, GoogleNet and ResNet [11-13]. But, the classification rate of these techniques depends on the training procedure depending on an adequate number of samples. Also, the major problem with EL imagery is the process of interpretation. This is done mostly by specialists who examine each EL picture taken manually. This technique generally takes a lot of time and needs properly skilled personnel. Manual inspection is therefore not sufficiently effective in large-scale manufacturing facilities and power plants [14]. So, automated processing of EL photos using deep learning models has become an important research field. In recent years, a lot of effort has been dedicated to PV module fault detection and analysis via EL imaging and deep learning models. From this viewpoint, this paper studies a detailed survey of different deep learning models for solar cell defect identification and categorization from EL images. In addition, a comparative study is presented to address the benefits and drawbacks of those models in order to recommend further improvement in the efficiency of categorizing solar cell defects in the EL images.

The remaining parts of this paper are structured as: Section 2 discusses various deep learning models developed for solar cell defects identification and categorization. Section 3 presents the benefits and drawbacks of those models. Section 4 summarizes this study and recommends further developments.

2. SURVEY ON SOLAR CELL DEFECTS IDENTIFICATION AND CATEGORIZATION MODELS

Ahmad et al. [15] presented automated categorization of PV cell defects in EL images. In this model, feature mining-based Support Vector Machine (SVM) and CNN were considered. Also, appropriate hyper-parameters, model optimizers and loss factors were applied to achieve better efficiency. The solar cell defects were split into different categories. Feature mining methods like HoG, KAZE, Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) were applied for learning the SVM classifier.

Su et al. [16] developed a new Complementary Attention Network (CAN) by integrating the new channel-wise attention subnetwork with the spatial attention subnetwork sequentially, which adaptively suppresses the background noise characteristics and identifies the defect characteristics concurrently. In this model, the new channel-wise attention subnetwork was used to apply a convolution process to integrate the aggregated and discriminative outcome characteristics extracted by the global mean pooling unit and max-pooling unit. Also, a Region Proposal Attention Network (RPAN) was applied by embedding CAN into a Region Proposal Network (RPN) for extracting more refined defective region proposals, which was applied to create a new end-to-end faster RPAN-CNN model to identify defects in raw EL images.

Espinosa et al. [17] developed a technique of automated physical defect categorization for PV plants using CNN for semantic partition and categorization from RGB pictures. In this technique, 2 primary processes were executed, namely solar panel identification and fault categorization. Initially, the panel objects were extracted from the RGB images of a solar panel array by CNN, which eliminated the background artifacts. After that, the fault identification and categorization were performed by a similar CNN.

Tang et al. [18] suggested a deep learning-based defect identification of PV units using EL photos by offering a huge amount of high-quality EL photo creation scheme and an effective framework for automated defect categorization with the created EL photos. First, the EL photo creation scheme was applied to merge standard image processing techniques with GAN properties to create the EL samples with high resolution. After that, the CNN-based structure was utilized for extracting the deep characteristics from an EL sample and automatically categorizing defects in an EL sample. Alves et al. [19] developed a common CNN structure to categorize various types of defects and degradation modes in PV cells. Also, sampling techniques with augmentation was utilized to normalize the number of samples in all classes in an unbalanced dataset.

Hwang et al. [20] developed a hybrid method with different embedded training schemes for improving the recognition of malfunctioning PV units with validated performances. First, the improved gamma correction operation was merged with the CNN for pre-processing. Then, IR photos of solar units were utilized for learning the pre-processing scheme. Also, the CNN structure was learned by the IR temperatures of PV units with the pre-processing of a threshold factor. After, the compression process was employed to cut the moment-intensive pre-processes. Moreover, the CNN was substituted with the XGBoost algorithm and the chosen temperature statistics.

Zhang et al. [21] designed a Multi-Feature RPN (MF-RPN) model for identifying surface defects. In this model, region proposals were extracted from various feature units of CNN. Also, considering that several aspect rates, scale configurations and the utilization of many RPNs results in an overlap of candidate areas and tend to cause data redundancy, a Multiscale Region Proposal Selection Strategy (MRPSS) was developed to decrease the number of region proposals and increase the system accuracy.

Wang et al. [22] developed an adaptive method to automatically identify and categorize the solar cell defects depending on absolute EL images. Initially, an unsupervised scheme was employed for identifying defects referring to the defect characteristics in EL pictures. After that, a diagnosis mechanism was adopted which statistically categorizes the identified defects depending on the electrical origin.

Demirci et al. [23] developed a new automated defect identification and categorization model for PV cells. First, data augmentation was applied to increase the number of training images and features were extracted by various pre-trained deep network structures such as DarkNet-19, ResNet-50, VGG-16 and VGG-19. After that, such extracted features were merged together. Also, a minimum Redundancy Maximum Relevance (RMR) scheme was applied to choose the optimal features.

Then, SVM was used to classify the PV cell defects. Further, a Lightweight CNN (L-CNN) structure was designed and learned from scratch without initial weights.

Deitsch et al. [24] designed a robust automated partition model to extract individual solar cells from EL photos of PV units. In this model, a mutual camera lens distortion measure and PV unit grid recognition were used to detect the accurate solar cell area.

Also, a robust initialization method was developed for the applied lens distortion framework. Moreover, a highly precise pixel-wise categorization was integrated into the active solar cell region on monocrystalline and polycrystalline PV units, robust to different standard defects in solar units.

Lin et al. [25] developed an automated cell partition method and a CNN-based defects recognition model with pseudo-colorization of defects. Initially, an automated cell partition method was employed for extracting cells from an EL photo.

Then, defect recognition was actualized through a CNN-based defect identifier and was visualized with pseudo-colors. For cell partitioning, contour tracing was used to precisely localize the panel area, and a probabilistic Hough transform was used to detect gridlines on the extracted panel area. Further, the defected defects were imposed with pseudo-colors to improve defect visualization by K-means clustering. Finally, the defects were identified by using YOLOv4 and categorized by the ResNet50.

2.1 Comparative Study

In this section, a comparative analysis of the merits and demerits of different deep learning models for PV cell defects classification whose operational details are studied in above section is presented in Table 1.

Table 1. Comparison of Different Deep Learning Models for PV Cell Defects Identification and Categorization

Ref. No.	Models	Merits	Demerits	No. of Images	Performance
[15]	Feature mining-based SVM and CNN	Improved efficiency and reliability.	It needs a large labeled EL images for each category of defects.	2624 EL images	Accuracy (%): HoG-SVM=69.95; KAZE-SVM=71.04; SIFT-SVM=68.9; SURF-SVM=72.74; CNN=91.58
[16]	Novel faster RPN-CAN	Maximum categorization efficiency.	Time consumption was high since the reduction rate in CAN was set manually.	2129 EL defective images and 1500 usual images	Precision=99.17%; Recall=97.78%; F-score=98.47%
[17]	CNN	Better efficiency for relatively small dataset.	Needs large set of images and tuning of classifier parameters.	200 images	Recall=0.5105; Precision=0.5039; F-score=0.5
[18]	GAN and CNN	Improved accuracy.	Requires different categories of cell defects to increase the efficiency.	1800 EL images	Accuracy=83%
[19]	CNN with augmentation	Less computational cost.	Identification accuracy was not efficient.	20000 IR images	Accuracy (for detection)=92.5% Accuracy (for classification)=78.85%
[20]	CNN and XGBoost	High effectiveness.	Needs larger datasets to limit irregularity.	684 images	Accuracy=99.2%
[21]	MF-RPN and MRPSS	Higher accuracy.	Longer identification time.	1461 solar cell images	Mean average precision=85%; Accuracy=97.83%
[22]	Adaptive unsupervised method	Reduced mean uncertainty.	Needs to improve the accuracy towards multiple defects.	GaAs solar cells	Accuracy=94.48%
[23]	Minimum RMR, SVM and L-CNN	Better efficiency.	It suffers from the imbalanced class distribution.	2624 EL solar cell images	Accuracy=94.52%
[24]	Robust automated partition and pixel-wise categorization	High robust and accurate.	There was an imprecise partition due to the consideration of ridges without evaluating entire image which causes spurious edges.	408 solar cell images	Accuracy=97.8%; F1-score=97.62%
[25]	CNN with pseudo-colorization, YOLOv4 and ResNet50 classifier	Highly precise for limited training images.	It does not identify the small defect around cell edges.	119 panel images and 7140 cell images	Accuracy=99.8%

3. CONCLUSION

In this paper, a survey on recent deep learning algorithms for the identification and categorization of PV cells defects was presented.

Additionally, their merits and demerits were investigated to recommend future enhancements. According to this comparative study, all researchers have been experienced in identifying and classifying the solar cell defects or cracks from EL images using deep learning models. Among those models, YOLOv4 and ResNet50-based model has the maximum accuracy compared to all other deep learning models for identifying and categorizing PV cell defects. Though it is highly precise for a limited amount of training samples, it is not able to identify the small defects around the cell boundaries. As a result, future work could be a focus on identifying and categorizing the small defects around the solar cell edges effectively using advanced transfer learning-based deep learning models.

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