Deep Learning-based Photovoltaic Panels Defect Detection Using Aerial Thermography Imaging

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***Abstract*—Photovoltaic (PV) power generation has grown exponentially in recent decades. Therefore operation and maintenance of PV systems to obtain optimal performance and extend the PV panels' lifetime become extremely important. Cost-effective and time-saving, aerial thermography has become a practical reliability assessment technique for large-scale photovoltaic power plants. Nevertheless, in real aerial thermography images of PV panels, some overheated regions or faults in PV modules are extremely small and difficult to identify. This work proposes a method based on deep learning to increase the accuracy of PV defect detection using aerial thermography imagery. To evaluate the performance of the proposed algorithm, a dataset of IR images of real PV power plants was used. The experimental results of the proposed model on the 2-class test dataset are 94.9 % accuracy, 95.3 % precision, and 96.5 % recall.**

***Index Terms*—Aerial thermography, PV modules, deep learning, Fault detection.**

I. Introduction

Photovoltaic (PV) power generation has increased tremendously over the past few decades, but its performance and dependability remain a concern regarding its integration into the power grid. In order to gain optimal performance from the PV system over its lifespan, regular inspection and maintenance of PV modules are important as the use of solar PV generation increases [1]. Consequently, it is necessary to develop techniques for inspecting and detecting faults in a PV system in a reliable, rapid, and efficient manner in order to discover and repair module failures in a timely manner to extend their lifetime and maintain the system's normal operating efficiency [2]

Electroluminescence (EL) imaging [3], infrared (IR) imaging [4], and electrical measurement and characterization [5] are a few of the known inspection techniques for fault detection in PV modules and cells. The visual inspection techniques, notably IR and EL, have been shown useful for identifying the precise location of defects. However, EL, typically used on a small scale and requires an indoor measurement, is impractical for large-scale outdoor applications like solar farms. On the other hand, infrared imaging is ideal for large-scale applications due to the instrument's small size and minimum requirements.

Infrared (IR) imaging permits using thermographic pictures to detect hot areas on photovoltaic (PV) modules and other hotter PV module components. This makes it possible to inspect the PV modules for defects like hot spots, connectivity issues, internal short circuits, and cell cracks. One disadvantage of conventional IR imaging is that it is extremely time-consuming to check a large-scale solar farm. A thermography inspection expert is also required to assess and verify PV module problems.

The conventional visual monitoring process of the PV system relied completely on human capabilities, and it took a significant amount of time to accomplish data collecting tasks, particularly in large PV power plants. In addition, human errors frequently affected this method when identifying the cause of PV system failure. In addition, current PV inspection techniques cannot provide online information on failures in monitored plants. Unmanned aerial vehicle (UAV) inspection of PV plants is a novel application for detecting defects and failures in PV modules. This approach technology is far more efficient, reliable, and cost-effective than conventional visual monitoring. Additionally, this inspection method can be utilized in high-risk human field regions, such as floating PV plants [6].

Due to the rapid development of machine learning, various deep learning (DL)-based techniques for PV defect identification and diagnostics have been proposed. Considering the successful implementation of deep learning in object detection and image classification [7], it may be possible to use DL in IR imaging to detect overheated areas in defective PV modules. However, in numerous real thermography images of PV panels, some overheated regions are small and vary in scale, particularly when aerial thermography imaging is used. It could potentially reduce the accuracy of defect detection. In this study, we present a DL model with high precision for aerial thermography inspection.

In section II, the dataset and methodology to build deep learning model are explained. Image processing for defect detection results and the corresponding discussion are described in Section III. Section IV presents the conclusion of this study.

II. Methodology

The approach of the proposed system for fault and defect detection on solar modules is discussed in this section. For the training and testing data of aerial thermography imaging, we utilize the public Infrared Solar Modules dataset, which was collected, categorized, and organized by [8], under the MIT license, and contains 12 different anomaly classes of PV thermographic images found in PV plants. This dataset contains 20,000 grayscale thermographic images at 24 by 40 pixels resolution. Mounted on UAV systems, a midwave or longwave

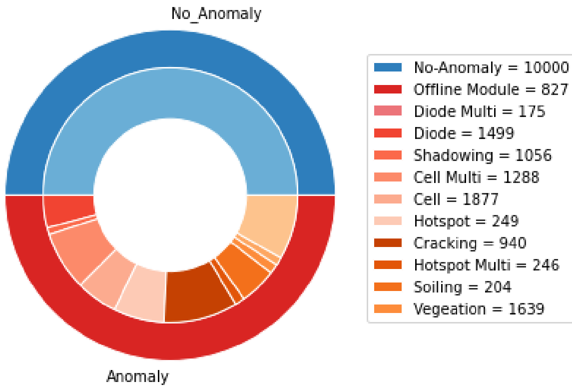

Fig. 1: Data distribution.

IR sensor (3-13.5 m) captured all images. Furthermore, this dataset also presents an unbalanced class distribution dataset, as shown in Figure 1.

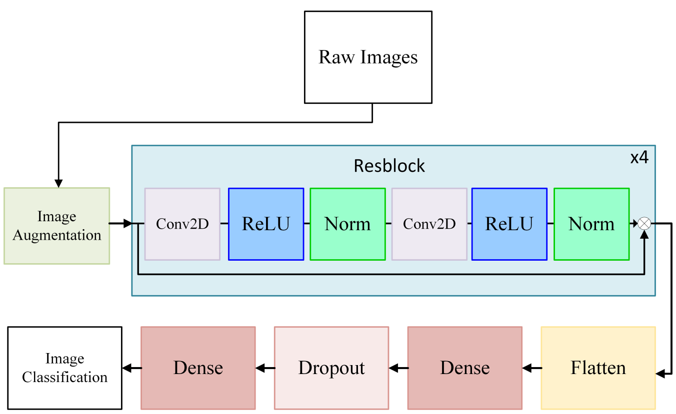

Fig. 2: Flowchart of machine learning.

Overall architecture to build a machine learning model depicts in Figure 2. The main structure of the framework is a series of Resblocks with different tuning. Oversampling and image augmentation, such as translation, flip, and brightness methods in the minority classes, are also implemented to improve the accuracy of the imbalanced dataset. The dataset was divided into 70% for training data, 20% validation data, and 10% testing data.

The performance metrics considered to evaluate the proposed algorithm are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

Where TP, TN, FP, and FN are the number of true positives, true negatives, false positives, and false negatives, respectively.

III. Result and Discussion

The model presented a 96.8% accuracy in the validation set, and 94.9% accuracy in the test set. Accuracy, precision, and recall on the test dataset and comparative study can be seen in the table below.

TABLE I: Comparison of the performance results using same dataset

Method	Accuracy	Precision	Recall
Fonseca Alves et al [1]	92.5%	92.0%	92.0%
Proposed method	94.9%	95.3%	96.5%

IV. Conclusion

This paper proposed a CNN model to detect defects in the PV panels using 20,000 real IR image data. The proposed CNN model provides 94.9% accuracy, 95.3% precision, and 96.5%recall. Combining image augmentation and oversampling methods improves the accuracy of the unbalanced dataset.

In our future work, we will classify PV panel faults using a deep neural network model with a 12-class output. We will also examine the combination of IR and CCD cameras to create a more robust and accurate model. Investigation of the implementation of a real system is also important.

V. Acknowledgment

This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program(IITP-2022-2018-0-01396) supervised by the IITP(Institute for Information & Communications Technology Planning & Evaluation).

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