AI-Based PV Panels Inspection using an Advanced YOLO Algorithm

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Abstract. The rapid growth of solar photovoltaic (PV) systems as green energy sources has gained momentum in recent years. However, the anomalies of PV panel defects can reduce its efficiency and minimize energy harvesting from the plant. The manual inspection of PV panel defects throughout the plant is costly and time-consuming. Thus, implementing more intelligent ways to inspect solar panel defects will provide more benefits than traditional ones. This study presents an implementation of a deep learning model to detect solar panel defects using an advanced object detection algorithm called You Look Only Once, version 7 (YOLOv7). YOLO is a popular algorithm in computer vision for classification and localization. The dataset utilized in this study was sourced from ROBOFLOW, consisting of 1660 infrared images showcasing thermal defects in PV panels. The model was constructed to identify a broader range of images with heterogeneity, leveraging the aforementioned dataset. Following validation, the model demonstrates a mean Average Precision (mAP) of 85.9%. With this accuracy, the model is relevant for real-world applications. This assertion is affirmed by testing the model with additional data from separate video-capturing PV panels. The video was recorded using a drone equipped with a thermal camera.

Introduction

The increase in energy demand due to massive population growth and the requirement to minimize greenhouse gas emissions have motivated novel approaches to utilizing more clean and sustainable energy. Solar energy is one of the most abundant renewable energy sources. It has now become popular due to the increase in its efficiency and lower cost compared to the last decades. However, maintaining photovoltaic modules is essential to maximize energy harvesting and gain more efficiency.

Defects in PV modules, whether arising from installation or operational factors, can significantly reduce their power generation efficiency. Despite features such as frames made up of Aluminum or glass-lamination that protect panels from environmental factors like rain, wind, and snow, they may not be able to completely protect panels from mechanical stress during transport or in extreme weather conditions like hail [1]. In addition, manufacturing defects such as defective soldering or faulty wiring can also affect the efficiency of PV modules [2]. Thus, it is vital to employ timely and dependable inspection methods to evaluate and uphold the peak functioning of PV modules, ensuring the utmost effectiveness of solar PV plants.

Implementing more intelligent ways of detecting PV panel defects is one of the most important topics to be discussed. Some researchers have implemented an AI-based method for detecting PV panel defects. Akram et al., for instance, proposed isolated deep learning techniques and developed model transfer deep learning techniques for the detection of PV module defects [3]. Both methods require low computational costs and less time, so they are suited for hardware with less memory installed. Herraiz et al. presented a novel approach to identifying PV panel defects using convolutional neural networks (CNN). They combined thermography and telemetry data to monitor panel conditions [4]. Various alternative strategies employing deep learning have been introduced for the identification of flaws in solar-cell panels. These strategies encompass the application of transfer learning methods utilizing various architectures such as VGG16 [5], VGG19 [6], GoogLeNet [7], ResNet18 [8], Unet [9], FPN [10], LinkNet [11], and EfficientNet [12] to identify anomalies on solar-cell panels [13].

This study delves into the application of an advanced Object Detection Algorithm, specifically YOLOv7, in the thermal inspection of PV panels. The utilization of AI through YOLOv7 aims to revolutionize the detection and classification of potential issues, offering a faster and more precise alternative to conventional inspection techniques. The choice of YOLOv7 architecture for this study is motivated by its reputation for real-time object detection capabilities. YOLOv7 works by dividing the input image into grids, enabling simultaneous prediction of bounding boxes and class probabilities, thus streamlining the detection process. This approach aligns with the demands of thermal inspection for PV panels, where swift and accurate identification of anomalies is crucial for maintaining the efficiency and reliability of solar energy systems. Furthermore, YOLOv7 performs single forward-pass neural networks, thus making it faster and more efficient compared to the other object detection algorithms.

The remaining parts of this paper are organized as follows: Section II presents a comprehensive literature analysis, outlining existing approaches for PV panel inspection and emphasizing advances in AI applications for similar goals. Section III describes the materials and methods utilized in the implementation of the YOLOv7 architecture for thermal inspection, including the dataset and training procedure. Section IV includes the experiment data and analysis, evaluating the performance of the proposed AI-based thermal inspection approach. Section V finishes the work with a summary of major findings, consequences, and future research directions.

Literature Review

Recently, machine learning has grown in popularity as a method for studying PV panels. Various researchers used different ways to inspect and maintain the quality of PV panel modules. Visual inspection, current-voltage (I-V) curve analysis, infrared thermography, and Electroluminescence (EL) testing are among these methods. For instance, in [14], the author utilized a multi-scale CNN model in two modes: transfer learning-based (using two selected DNNs) and independent light-depth (CNN-ILD) CNN. The experimental data using the open ELPV dataset shows promising classifications for PV panel defects in EL images. However, the EL imaging system assesses the photovoltaic (PV) system in low-light conditions, concurrently administering a direct current (DC) to the PV. This approach enables the detection of minor defects, disconnected cell regions, shunts, and similar issues within the PV cells, making it well-suited for indoor inspections. Nevertheless, employing this method outdoors for extensive objects presents notable challenges [15].

Many researchers have also used other types of machine learning to classify solar panel flaws according to attributes extracted from EL images, including Support Vector Machines, Random Forests, and K-Nearest Neighbors [16], [17], and [18]. These methods require manual feature extraction, in which relevant features that capture the traits of various fault kinds are designed using domain expertise. However, these approaches' effectiveness usually depends on how well-

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engineered the features are, so they could not be as effective as deep learning approaches, in which the features can automatically learned. [19] and [20]. Similarly, several research studies have been done on deep learning techniques for detecting PV panel defects using EL and IR images. For example, in [15], the author proposed a remote sensing method using infrared radiation cameras installed on unmanned aerial vehicles (UAV) to capture images of solar panels and detect anomalies using CNN. Likewise, [21] proposed a deep-learning method to detect defective solar panels in EL images. They utilize two CNN architectures: a fine-tuned VGG16 model for classification and a lightweight CNN model created from scratch for baseline comparison. The proposed method achieved a 95.2% accuracy on the test dataset. However, these approaches have their limitations. The fine-tuned VGG16 model, while effective in classification, may face challenges in real-time performance, potentially hindering its practicality for dynamic PV panel inspections. On the other hand, the lightweight CNN model, though created for efficiency, might struggle to achieve the same level of accuracy as more established architectures, impacting its reliability in defect detection tasks. These drawbacks influenced our decision to explore alternative solutions better suited for the real-time and accuracy demands of our project.

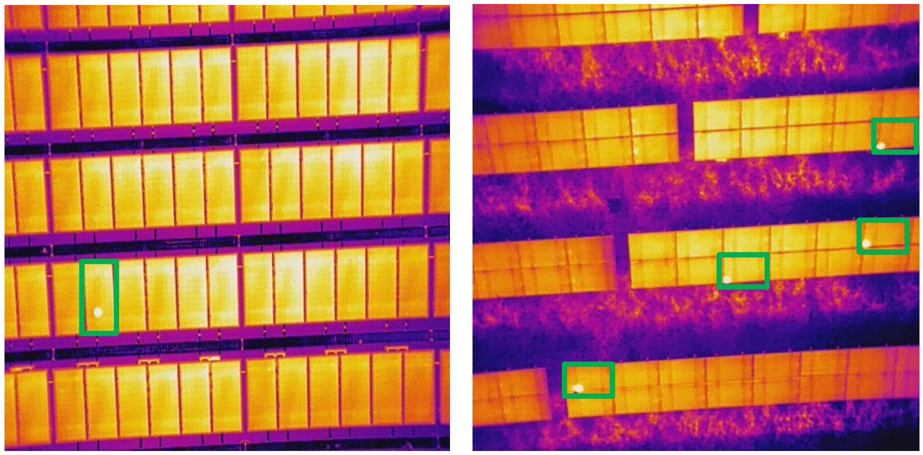
While several research studies have delved into deep learning techniques for detecting defects in PV panels using EL and IR images, our focus on thermal IR image-based defect detection led us to explore alternatives better aligned with the real-time and accuracy demands of our project. Contrary to the drawbacks associated with the existing methods mentioned above, we opted for YOLOv7 for several reasons. Compared to [15], YOLOv7 provides better object recognition performance for outdoor PV panel inspection, with higher label assignment and bounding box localization. YOLOv7 is also based on neural network architectures that require no feature selection, as mentioned in [16], [17], and [18], which are based on Machine Learning models. The last thing to note here is that, compared to other deep learning models such as mentioned in [21], YOLOv7 requires much less computational cost, making it learn much faster with smaller datasets without pre-training needed. [22].

Methodology and Experiments

The dataset for this project was obtained from ROBOFLOW, an online resource for open-source datasets for computer vision. The dataset comprising thermal images of PV panels acquired by UAV was downloaded in YOLOv7 format. The dataset contains 5313 labeled images [23]. The label contains a bounding box information of the object, such as x-center, y-center, height, width, and the PV panel's status. This format is required for YOLOv7 to detect the object and do localization. Before training the model, the dataset was pre-processed. We chose only 1660 images for this study and removed those images that were taken from a short-distance shoot.

The dataset was then split into training, validation, and testing with a ratio of 70%, 20%, and 10% for training, validation, and testing, respectively. During the training process, we used only the training and validation dataset, while we reserved the testing dataset for testing unseen data.

Fig. 1a shows a sample PV panel thermal image with a single hot spot, while Fig. 1b shows the PV panel with a multi-hot spot. The brighter spots in the panels are the defective cells of the panel due to heat dissipation, and this phenomenon can decrease the efficiency of the panel. All the image sizes are 640x640 pixels.



(a) (b)

Fig. 1 Sample of images. (a) Image with single hotspot. (b) Image with multiple hotspots [23].

YOLOv7 is the most updated version of the YOLO family from the original authors of the YOLO architecture. This model outperformed all known predecessor object detectors in speed and accuracy, such as YOLOR, YOLOX, YOLOv5, Scaled-YOLOv4, and PPYOLOE. It has reduced a significant number of parameters and computational costs, leading to faster inference speeds and higher detection accuracy. The Basic YOLO Architecture is described in Fig. 2, and the YOLOv7 introduced some major changes in its new architecture, including the Extended Efficient Layer Aggregation Network (E-ELAN), compound model scaling, planned re-parameterized convolution, and coarse-to-fine lead guided assigner [24].

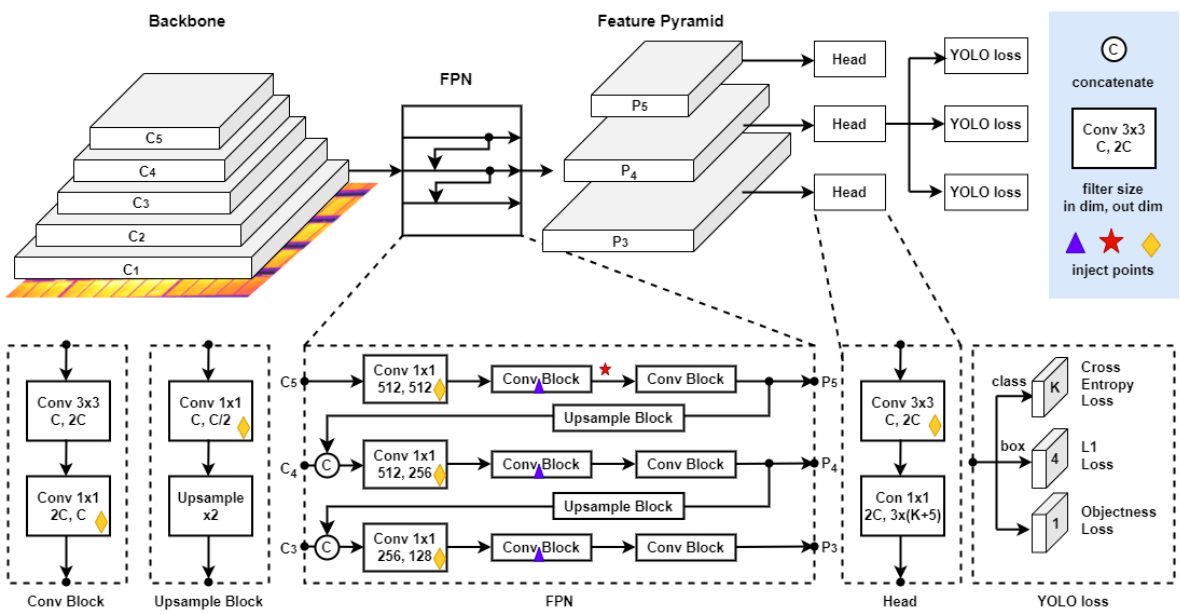


Fig. 2 Basic YOLO Architecture [25].

In this study, we built the model based on YOLOv7 using the mentioned dataset. We used the Nvidia GPU to accelerate the training process and a specific project directory in Google Drive mounted to the Google Colab. All the datasets were put in this directory. The original YOLOv7 repository and the pre-trained model were then acquired. With some adjustments to the dataset and label information in the COCO.yaml and YOLOv7.yaml files, the models were then trained. The parameters used during the experiment can be seen in Table 1. The Performance metrics we used to evaluate the accuracy of the model's performance are mAP, precision, and recall. Mean Average Precision (mAP) is commonly used to evaluate the model, with ranges of the evaluation from 0 to 1. On the other hand, we also use precision to indicate the accuracy of the detected objects, calculating how many detections were correct, while recall gives information about the ability of the model to identify all instances of objects in the images.

Table 1. Training parameters of the models.

Batch Number	Learning Rate	Momentum	Weight Decay	Number of epochs
8	0.01	0.937	0.0005	200

Result and Discussion

The objective was to evaluate the model's accuracy and investigate its performance in real-life applications. The model was built using heterogeneous images with different elevation drone cameras and more angles. When we test the model using testing data, it can be seen that the model can detect PV panel defects from various images. The data was split into 1170 training data points, 330 validation data points, and 160 testing data points. The batch size was 8, with a learning rate of 0.01, a momentum of 0.937, a weight decay of 0.0005, and a running of 200 epochs. After running the testing with the best weight, it yielded the mAP of 85.9% for threshold 0.5 IoU, the R-value of 83.2%, and the P-value of 75.9%, with 322 defect panels detected from 160 images, as described in Tabel 2. The sample of the testing image was used to see the performance of the model in detecting PV panel defects, as we described in Fig 3. It can be observed that the model performed well in detecting PV panel defects, with three bounding boxes detected with an IoU of 0.71, 0.79, and 0.80.

Table 2. Testing Result of the Model.

Images	Labels	Precision	Recall	mAP@0.5
160	322	0.759	0.832	0.859

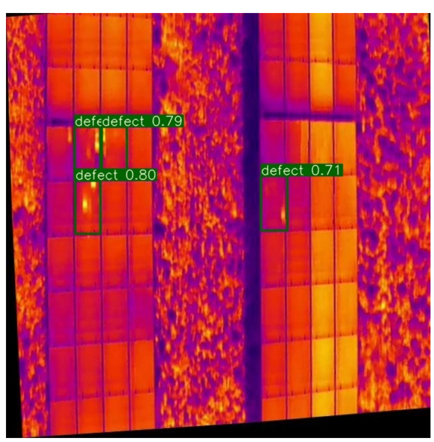
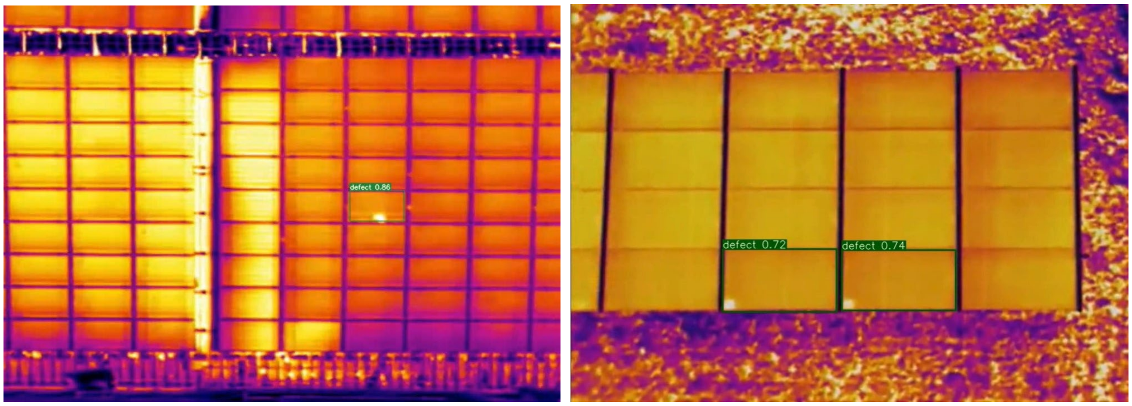


Fig. 3. Model performance for the testing image.

To see the performance of the models for a real-life application, the model was tested to run on a video file obtained from [26]. It was found that the Model performed well in the detection of PV panel defects, as can be seen in Fig. 4. This Model can also be applied for the online monitoring of PV panel defects when it is used to detect the panel using a drone-embedded camera during PV panel inspection.



(a) (b)

Fig. 4. Model performance on the testing videos.

Conclusion

Solar energy is one of the most popular renewable energy resources, and many countries are now utilizing photovoltaic (PV) panels to harvest energy from the sun. However, the occurrence of PV panel defects can reduce its efficiency and decrease power output. To address this challenge, a lot of research has been conducted to alternate manual PV panel inspection with the most effective and intelligent methods. This study presented an implementation of artificial intelligence, especially deep learning architecture for object detection, known as You Look Only Once, version 7 (YOLOv7). The object detection model was developed using a dataset comprising 1660 data points, achieving an mAP of 85.9%. The model can effectively learn a diverse set of images suitable for real-life applications. This capability was confirmed during testing on unseen images, where the model demonstrated good performance. Furthermore, the model underwent evaluation with a video file for real-life applications. To extend this study to future works, the model can be developed with more heterogeneous images with variations in elevations and angles to perform much better for online applications, especially when it comes to deploying the system in edge artificial intelligence environments.

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