A Novel Approach for PV Cell Fault Detection using YOLOv8 and Particle Swarm Optimization

Quoc Bao Phan ¹ and Tuy Nguyen ²

¹Affiliation not available
²Northern Arizona University

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Abstract

This paper presents a novel approach for detecting faults in photovoltaic (PV) cells. The proposed method combines the power of You Only Look Once version 8 (YOLOv8) and Particle Swarm Optimization (PSO) architecture. Unlike existing methods, the proposed model leverages PSO to optimize the parameters of YOLOv8, enhancing detection accuracy. To evaluate the efficacy of the proposed approach, two experimental cases are conducted, one with a 70% training set and the other with an 80% training set. The PV system data is used as input for the model, and YOLOv8 is utilized to extract necessary features before detecting fault cells from the data. We use PSO algorithm to optimize the model’s parameters to achieve the best detection accuracy. The experimental results demonstrate that the proposed approach achieves the highest mean Average Precision (mAP) of 94% at an intersection over union (IoU) threshold of 0.5, outperforming existing fault detection methods in terms of accuracy and robustness. Moreover, by leveraging the power of YOLOv8 and PSO, the approach offers a promising solution for reliable and efficient fault detection in PV systems, thus making it a practical solution to enhance the system’s performance and reduce maintenance expenses.
A Novel Approach for PV Cell Fault Detection using YOLOv8 and Particle Swarm Optimization

Quoc Bao Phan and Tuy Tan Nguyen

School of Informatics, Computing, and Cyber Systems
Northern Arizona University
Flagstaff, AZ 86011, USA
tuy.nguyen@nau.edu

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Index Terms—PV cell fault detection, deep neural network, YOLOv8, optimization

I. INTRODUCTION

The detection of defects in solar panels is an important and evolving issue, particularly with the increasing adoption of renewable energy. Conventional fault detection methods typically rely on data analysis, I–V curve analysis, and thermal chart simulations, as described in [1]–[4]. However, these methods can be challenging to implement as they require a certain level of expertise to analyze and diagnose errors. Moreover, these faults are frequently only discovered after the solar panel has encountered an issue, resulting in energy loss or even damage to distribution circuits. Consequently, these methods are associated with technical and maintenance challenges.

To address these challenges, researchers have been exploring the use of machine learning algorithms to automate the detection of defects in solar panels and improve the reliability and efficiency of photovoltaic (PV) systems. The studies of Kabir et al. [5] utilized tree-based models, while An et al. [6] employed statistical models, and Yi et al. [7] used Support Vector Machines (SVM) for fault classification and identification. However, the accuracy of these methods has not been optimal. On the other hand, deep learning methods have been utilized in other studies, such as Gao et al. [8] and Al et al. [9], while others rely on image capture methods using solar panels that have been in operation for some time. These methods have been significantly effective and innovative, as they can diagnose faults in solar panels early, even before the problem has a significant impact on the energy system. This can help operators to have maintenance and repair plans in place in advance, rather than dealing with the unwanted consequences of failures. Furthermore, You Only Look Once (YOLO) version 5, as demonstrated in [10]–[12] or other variants, has shown impressive capabilities in object recognition tasks.

In this study, we focus on developing a fault detection model based on actual images using the latest version of YOLO, YOLOv8, which was developed in early 2023. Additionally, the Particle Swarm Optimization (PSO) algorithm is used to find the optimal parameters for the recognition model. The data set includes over 2,000 images of solar panel cells with corresponding labels, divided into training and testing sets for the model’s input.

The remaining of this paper is structured as follows. Section II introduces the system implementation. Data collection and preparation are described in Section III. Section IV presents experimental results, followed by the conclusions in Section V.

II. SYSTEM IMPLEMENTATION

A. Particle Swarm Optimization

PSO is a popular metaheuristic optimization technique that simulates the behavior of a swarm of particles moving in a search space to find an optimal solution to a given problem. PSO was first proposed by Kennedy and Eberhart in 1995 [13], [14] and since then, it has become one of the most widely used optimization algorithms in various fields, including engineering, finance, biology, and many more.

The basic principle of PSO is inspired by the social behavior of animals, specifically the flocking and swarming behavior of birds and fish. Each particle in the swarm represents a potential solution to the problem, and its movement is influenced by its own experience as well as the experience of its neighbors. The particles in the swarm move around the search space in search of the optimal solution by adjusting their positions and velocities according to certain mathematical
formulas. Additionally, PSO can also handle both continuous and discrete optimization problems, which makes it a versatile optimization algorithm.

This study utilized PSO to optimize the learning rate, batch size, anchor box size, and input image size of the YOLO model to maximize the mean average precision at an intersection over a union (IoU) threshold of 0.5.

B. Objective Detection Model

YOLO is a state-of-the-art object detection algorithm that was first introduced in [15], which uses a deep neural network to detect and localize objects in an image. The objective of YOLO is to predict bounding boxes and class probabilities for each object in the input image. YOLO has demonstrated its high performance in object detection and localization on various datasets. The YOLO algorithm has also been extended to real-time object detection applications, making it a popular choice for object detection in video streams and robotics applications.

The YOLOv8 architecture can be shown in Fig. 1 and broken down into several main components, which are described as follows:

- **Backbone network**: The backbone network is responsible for extracting features from the input image. In YOLOv8, the backbone network is based on the cross-stage partial network (CSPNet) architecture to reduce the computational cost of the network while maintaining its accuracy.

- **Neck**: The neck is a network that connects the backbone to the detection head. In YOLOv8, the neck is a spatial pyramid pooling (SPP) module, which uses different pooling sizes to capture features at different scales.

- **Detection head**: The detection head predicts the bounding boxes and class probabilities for each object in the input image. In YOLOv8, the detection head consists of several convolutional layers, followed by a set of anchor boxes that predict the bounding boxes and class probabilities for each object.

- **Loss function**: The loss function in YOLOv8 combines several terms, including the objectness loss, the classification loss, and the bounding box regression loss. The objectness loss penalizes incorrect predictions of objectness, which indicates whether an object is present in a particular location.

- **Post-processing**: After the detection head has predicted the bounding boxes and class probabilities, YOLOv8 applies non-maximum suppression to remove redundant bounding boxes and select the most probable ones. It also uses anchor boxes to refine the predicted bounding boxes and improve the accuracy of the final detections.
III. DATA COLLECTION AND PREPARATION

The data set used in this study consists of 2,624 grayscale images of solar cells, each with dimensions of 300×300 pixels, collected by Buerhop-Lutz, et.al [16]. The images depict functional and defective solar cells with varying degrees of degradation, extracted from 44 different solar modules. The data set was collected using electroluminescence (EL) imaging, a non-invasive technique for visualizing the performance of solar cells. EL imaging provides a high-contrast image of the solar cell, revealing any defects that may be present. The images in the data set were annotated to identify the location and type of defects present in the solar cells. The defects were categorized as intrinsic or extrinsic, depending on whether they originated from within the solar cell material or from external factors such as handling or installation.

To ensure consistency in the data set, all images were normalized with respect to size and perspective. This involved scaling and cropping the images to ensure they were of the same size and orientation. Additionally, any distortion induced by the camera lens used to capture the EL images was eliminated prior to solar cell extraction. This was achieved using standard image processing techniques, including geometric correction and image enhancement. The overview of the input data set is shown in Fig. 2.

IV. EXPERIMENTAL RESULTS

A. Training Phase

In this study, we aim to compare the performance of the latest YOLO object detection model versions, YOLOv7 and YOLOv8, and investigate the impact of different training ratios on the model performance. YOLOv7 and YOLOv8 introduce several improvements over the previous versions, such as a more powerful backbone network, improved anchor box design, and better feature fusion.

To evaluate the performance of the two models, we divide the data set into training, validation, and testing sets, with training ratios of 70% and 80% for both YOLOv7 and YOLOv8. The model parameters, including learning rate, batch size, anchor box size, and input size, are optimized using the PSO method.

In our PSO implementation, the maximum number of iterations (max inter) is set to 50, and the optimization function is to maximize mAP@50, where mAP@50 measures the mean average precision of the model at an IoU threshold of 0.5. We also evaluate the model performance using other metrics, such as F1 score, Precision-Recall curve, and mAP@50-95.

In a confusion matrix, the rows represent the true classes of the objects, and the columns represent the predicted classes. Since the background class refers to all the pixels in the image that are not part of any object, it is not a class that the YOLO model is trained to detect. Therefore, when the model is applied to an image, it should not predict any objects belonging to the background class. As a result, in Fig.3, the confusion matrix of the YOLO models will always be 0 in the background-background column because it is not a valid prediction for the model to make.

The optimized results for each case are presented in Table I. Fig. 4 shows the F1 and precision-recall curves for the case of a training ratio of 0.8, demonstrating the impressive training ability of the YOLOv8 model. With epoch = 100, the loss parameters tend to converge toward their minimum values, the precision, recall, as well as the mAP@50, and mAP@50-95 scores all tend to increase with the number of epochs.

B. Object Detection Results

The results of the error detection are shown in Fig. 6, where most of the errors were detected with a model confidence level set at 0.7. However, as the input images were in black and white, this may have had some impact on the detection ability. Additionally, a comparison between the two YOLO models is presented in Table II. The observations of Table II and Fig. 6 can be listed as follows:

- Both YOLO models offer good error detection capabilities, with mAP@50 and mAP@50-95 scores above 70% in all cases.

<table>
<thead>
<tr>
<th>Test Case</th>
<th>Learning rate</th>
<th>Batch size</th>
<th>Anchor box size</th>
<th>Input size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of 0.7</td>
<td>YOLOv7</td>
<td>0.001</td>
<td>16</td>
<td>64</td>
</tr>
<tr>
<td>Ratio of 0.8</td>
<td>YOLOv7</td>
<td>0.0001</td>
<td>32</td>
<td>128</td>
</tr>
<tr>
<td>Ratio of 0.7</td>
<td>YOLOv8</td>
<td>0.0001</td>
<td>32</td>
<td>64</td>
</tr>
<tr>
<td>Ratio of 0.8</td>
<td>YOLOv8</td>
<td>0.0001</td>
<td>32</td>
<td>128</td>
</tr>
</tbody>
</table>

Table I: HYPERPARAMETER TUNING

Fig. 3. The confusion matrix of 0.7 (left) and 0.8 (right) ratio.

Fig. 4. F1 and PR curve with training ratio of 0.8 of YOLOv8 model.
Table II

<table>
<thead>
<tr>
<th>Test Case</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>mAP@50</th>
<th>mAP@50-95</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.7</td>
<td>YOLOv7</td>
<td>0.77</td>
<td>0.73</td>
<td>0.75</td>
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<tr>
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<td>0.85</td>
<td>0.81</td>
<td>0.83</td>
<td>0.80</td>
</tr>
<tr>
<td>Ratio of</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.8</td>
<td>YOLOv7</td>
<td>0.83</td>
<td>0.82</td>
<td>0.82</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td>YOLOv8</td>
<td>0.94</td>
<td>0.91</td>
<td>0.92</td>
<td>0.94</td>
</tr>
</tbody>
</table>

- For this specific problem, the 80% training set ratio performs better than the 70% ratio, possibly due to the presence of difficult-to-detect objects in the data set, requiring more training data.
- The YOLOv8 model outperforms YOLOv7, with mAP@50 scores of 80% versus 75% for the 70% training ratio case, and 94% versus 88% for the 80% training ratio case as well.
- However, there are still some limitations as the detection accuracy is not yet perfect and there is still room for improvement in the future.

The models demonstrate high accuracy in PV fault detection, making it a promising approach to detecting PV faults before they have a negative impact on the PV system.

V. Conclusion

In conclusion, the use of AI in PV cell fault detection has been gaining increasing attention in recent years. This study contributes to this field by providing a comparison between the two latest YOLO models combined with the PSO algorithm. The results of the study indicate that both models perform well in terms of mAP scores, with YOLOv8 demonstrating a significant improvement in several metrics. These findings highlight the potential of YOLOv8 for accurate and efficient PV cell fault detection based on images. These findings can serve as a valuable reference for researchers and practitioners in this field and further improvements in the future.

ACKNOWLEDGMENT

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REFERENCES


