Solar Panel Defect Detection and Panel Localization Using Yolov5

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Abstract. Large-scale solar farms, often encompassing more than 100,000 panels, face significant challenges in maintaining optimal performance due to the impracticality of manual defect inspections. Undetected defects reduce panel efficiency, increase operational costs, and delay necessary maintenance, leading to more extensive damage and higher repair costs. This paper outlines a comprehensive approach to automatically detect defects and localize both normal and defective solar panels using the YOLOv5 model, addressing the need for efficient and reliable maintenance in large-scale solar farms. Initially, YOLOv5 is employed to classify specific zones within images containing two panels. Identified zones are cropped, and the same YOLOv5 model is used again to accurately localize each individual panel within the zone. Subsequently, the model is reapplied to detect any defects in the solar panels, analyzing and identifying anomalies. The panels and their defects are then precisely located, with bounding boxes drawn around the defect spots. The proposed method ensures thorough and precise identification and localization of both the panels and their defects. The final training results demonstrate near-perfect performance across all metrics, achieving a precision (P) of 0.947, a recall (R) of 0.968, and a mean Average Precision at 50% IoU (mAP50) of 0.989 for all classes. This project addresses critical challenges in the maintenance of large-scale solar farms, enhancing the efficiency and longevity of solar panels through timely and accurate defect detection. The automated system reduces labor costs, minimizes downtime, and promotes sustainable energy production. By fostering innovation in AI and image processing, the project contributes to technological advancements and supports global transitions to renewable energy sources. Future efforts will focus on real-time deployment on edge devices, integration with maintenance systems, expanding datasets for improved model robustness, and exploring multispectral imaging. Additionally, efforts will be made to integrate predictive maintenance algorithms, and conduct extensive field testing and long-term validation.

Keywords: Solar Panel, Defect Detection, YOLOv5, localization

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1 Introduction

Solar panels, those sleek, shining devices that capture sunlight and transform it into electricity [1], are more than just a technological marvel—they are a beacon of hope for a sustainable future. Picture fields of solar panels glistening in the sun, each one contributing to a greener planet by reducing the reliance on fossil fuels as solar panel carbon emission is 95% less than coal [2]. For governments, the benefits are manifold. By investing in solar energy, they can achieve greater energy independence, create jobs in the renewable energy sector, and lower energy costs for their citizens. Malaysian government incentives encourage widespread adoption, leading to a more resilient and sustainable energy infrastructure that can power homes and industries while protecting the environment [3].

However, the journey of solar panels from installation to energy production isn't without challenges. Like any technology, solar panels can develop defects over time—cracks, hot spots, or faulty connections that can severely impact their efficiency and longevity [4]–[6]. Detecting these defects early is crucial, akin to catching a cold before it turns into pneumonia. Timely detection allows for quick repairs or replacements, ensuring that each panel operates at its peak efficiency. This not only maximizes energy output and return on investment but also ensures a steady supply of renewable energy, aiding in meeting energy goals and reducing the carbon footprint.

Consider the vast solar farms with thousands of panels. Locating a defective panel in such a sea of technology is like finding a needle in a haystack. Accurate localization of defects is essential for efficient maintenance. When issues are precisely identified, technicians can quickly address them, minimizing downtime and reducing maintenance costs. For large-scale solar operations, this targeted approach is vital. It ensures that all panels function optimally, enhancing the overall energy output and reliability of the system.

This is where the power of machine learning comes into play [7]. Imagine a sophisticated system, equipped with advanced algorithms like YOLOv5 [8], tirelessly scanning through images of solar panels, pinpointing defects with unparalleled accuracy and speed. Unlike human experts who may experience fatigue and subjective judgment [9], machine learning models are relentless and precise. They can analyze vast amounts of data efficiently, continuously learning and improving from new information. This automation not only enhances the precision of defect detection but also accelerates the process, making maintenance more effective and ensuring higher efficiency of solar panel systems. In a world where renewable energy is crucial for our survival, integrating machine learning in solar panel maintenance is nothing short of revolutionary, bridging the gap between human limitations and technological potential.

In this research, we propose a method to identify defects and localize solar panels using YOLOv5. We will first use YOLOv5 to localize the solar panels before scanning them to identify defect spots. This paper comprises five sections: introduction, related review, methodology, results, and conclusion.

2 Related Review

This section provides an in-depth literature review of previously developed algorithms, offering insights into their methodologies and outcomes. It serves to highlight the unique aspects and contributions of this research by contrasting it with established methods. A total of five distinct methods are examined and compared in detail, with a summary of their characteristics and capabilities presented in Table 1. This comparative analysis underscores the advancements and innovations introduced by this research, situating it within the context of existing work in the field.

Table 1. Previous Research

Research/ Paper Title	Methods	Advantages	Disadvantages
A technique for fault detection, identification and location in solar photovoltaic systems [4]	Incorporate the current flow in the string within the solar panels	Automatic detection of line-wiring faults and localization	Assuming no faults string currents and compare it with actual string currents
Solar panel defect detection design based on YOLO v5 algorithm [10]	Use Yolov5 to classify defect spot	Efficient speed in detecting defective spots	No panel localization method introduced
Solar panel hotspot localization and fault classification using deep learning approach [6]	Use various deep learning and machine learning to classify fault and localize hotspot.	Eliminate use of human expert and allow early detection. Utilize advanced algorithms to classify hotspots and faults	The panel localization method lacks efficiency, effectiveness, and conciseness. It fails to focus adequately beyond identifying hotspots.
Fault detection and classification in solar based distribution systems in the presence of deep learning and social spider method [7]	Use generative adversarial networks (GANs) and Social Spyder method to detect fault.	Hybrid method which can increase classification capability	No panel localization method introduced
Solar Cell Surface Defect Detection Based on Improved YOLO v5 [11]	Use YOLO v5 to detect fault	Improve YOLO v5 to increase its capability	No panel localization method introduced

Firstly, the paper titled “A Techniques for Fault Detection, Identification, and Location in Solar Photovoltaic Systems” [4] introduces a comparative method for detecting faults. This approach involves comparing the actual current flow against an assumed fault-free current flow. While this method aids in fault detection and panel localization, its reliance on assumed fault-free conditions presents a limitation, as assumptions can undermine the capability of outlier detection [12].

Next, the paper titled “Solar Panel Defect Detection Design Based on YOLO v5 Algorithm” [10] utilizes the same algorithm as this study but incorporates enhancements that improve speed and reduce hardware energy requirements. Despite these advancements, the paper does not include a method for panel localization.

The paper titled “Solar Panel Hotspot Localization and Fault Classification Using Deep Learning Approach” [6] explores a range of machine learning and deep learning techniques, comparing their effectiveness and integrating critical automation to eliminate the need for human expertise. It employs these technologies to identify hotspot areas and subsequently locate the panels. However, the paper does not detail the method for determining the coordinates of these locations and focuses solely on hotspots. It does not address how defects in non-hotspot areas are handled or the implications of such defects.

The paper titled “Fault Detection and Classification in Solar-Based Distribution Systems Using Deep Learning and Social Spider Methods” [7] employs Generative Adversarial Networks (GANs) and the Social Spider method to identify defective panels. By integrating these hybrid techniques, the paper enhances the system's detection capabilities. However, it does not provide methods for panel localization.

Finally, the paper titled “Solar Cell Surface Defect Detection Based on Improved YOLO v5” [11] presents an enhanced version of the YOLO v5 algorithm, designed to bolster its detection capabilities. Despite these improvements, the researchers did not focus on panel localization, leaving the issue of identifying the exact location of defective panels unaddressed.

Therefore, in this paper, we introduce a groundbreaking technique that has not been explored before, aiming to advance both panel localization and defect detection with greater efficiency and effectiveness. This novel approach utilizes the YOLO v5 algorithm exclusively, setting a new benchmark in the field and encouraging further research into the precise localization of defective solar panels.

3 Methodology

This section outlines the methodology for localization and detection. We employ YOLOv5x to detect three distinct classes: zone, panel, and defect spot. The images used are thermal, as they highlight defects with white spots more clearly than standard images. The process begins with training the YOLOv5x model, followed by localization and identifying defect spots.

3.1 Data Collection and Dataset Preparation

For this study, data was collected using a drone to capture detailed thermal images of solar panels. The solar panels used in this research are owned by Tenaga Nasional Berhad Integrated Learning Solution (TNB iLSAS). Our dataset comprises 79 thermal images, which collectively include 193 panels, 76 zones, and 45 defect spots.

To ensure robust training and evaluation of our model, we split these 79 thermal images into training and testing sets. The training set consists of 63 images, while the testing set is composed of 16 images. This distribution ensures that 80% of the images are used for training and the remaining 20% for testing, providing a balanced approach to model validation.

The testing dataset specifically includes 7 defect spots, 39 panels, and 17 zones, ensuring that it is representative of the challenges the model will face in real-world scenarios. Table 2 provides a detailed breakdown of this split, highlighting the careful consideration given to maintaining a representative distribution of panels, zones, and defects in both the training and testing datasets.

Table 2. Data Distribution

Class	Training (80%)	Testing (20%)	Total Classes
Zone	59	17	76
Panel	154	39	193
Defect	38	7	45
Total Data	251	63	314

This structured approach to data collection and preparation is critical for training an effective model. By leveraging thermal imaging technology and systematically organizing our data, we can better train the YOLOv5 model to accurately detect and localize defects in solar panels, ultimately contributing to improved maintenance practices and energy efficiency.

3.2 Model Development and Training

First, we use a Kaggle notebook to develop the YOLOv5x model. We utilize labelling to annotate each class. Figure 1 illustrates the three classes that will be labelled and trained in the Kaggle notebook.

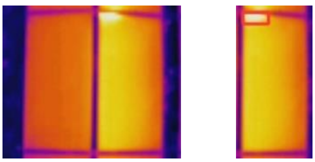

Fig. 1. The left image shows the zone, while the right image displays the panel with a red box indicating the defect spot

We conducted the training of the YOLOv5x model over the course of 700 epochs. This extensive training process was designed to ensure the model's accuracy and reliability in detecting and localizing defects in solar panels. The whole model is depicted in Fig. 2.

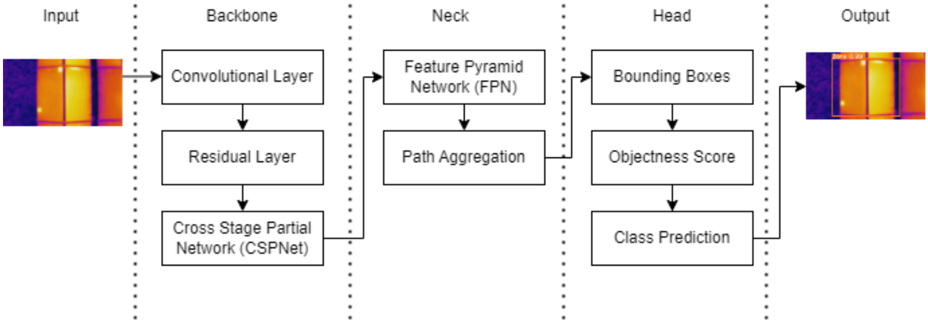

Fig. 2. The Model Architecture

Firstly, the training dataset enters the backbone layer. This layer consists of convolutional layers, which scan the images and identify patterns, residual layers, which retain information from earlier layers, and Cross Stage Partial Networks (CSPNet), which help learn better features from the images. Next, the data enters the neck layer, which includes the Feature Pyramid Network (FPN) to aid in detecting objects at various scales, followed by Path Aggregation to enhance the information exchange between large-scale and small-scale objects. The data then moves to the head layer, where bounding boxes are created for each predicted object. The objectness score indicates the model's confidence in detecting these objects, and class prediction labels the objects. The final output is a set of labeled images.

Our dataset was divided into two parts: 84% of the data was allocated for training, while the remaining 16% was set aside for testing. This split allowed us to effectively train the model while also evaluating its performance on unseen data. The detailed results of this training process, including performance metrics and evaluation outcomes, will be thoroughly discussed and presented in Section 3. This comprehensive approach ensures that the model is well-tuned and capable of accurate defect detection in practical applications.

3.3 Detection and Localization

The flow of detection and localization are shown in Fig.3.

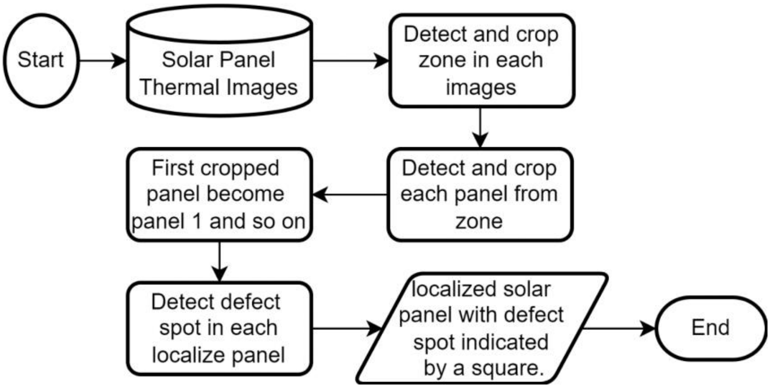

Fig. 3. Flow of localization and detection

After cropping the zones, the localization process begins, followed by the detection of defect spots. The final output will include data consisting of localized panels and identified defect spots, clearly indicating the areas of concern on the solar panels.

4 Results

We will discuss the training outcomes as well as the localization and detection processes.

4.1 Training Result

Table 3 shows the training result.

Table 3. Training Result

Class	Instances	Precision (P)	Recall (R)	Mean average precision (mAP50)
All	63	94.7%	96.8%	98.9%
Zone	17	84.1%	100%	97.8%
Panel	39	100%	94.3%	99.4%
Defect	7	100%	96.2%	99.5%

The training results for the model demonstrate its exceptional performance in accurately detecting and localizing zones, panels, and defect spots in solar panel images. For the zone class, the model achieved a precision of 84.1%, meaning it correctly identified 84.1% of defects. It also achieved a perfect recall of 1.0, meaning it successfully identified all actual zones in the images without any misses. The mean average precision (mAP50) for zones is 97.8%, reflecting the model's high accuracy and consistency in detecting zones.

In the panel class, the model's performance is even more impressive, with a precision of 100%, showing that all identified panels are correct with no false positives. The recall is 94.3%, showing it missed a small fraction of actual panels. The mAP50 for panels is 99.4%, demonstrating the model's reliability in accurately identifying panels.

For the defect class, the model achieved a precision of 100%, meaning all detected defects are true defects with no false positives. The recall is perfect at 1.0, indicating that the model identified all actual defects in the images. The mAP50 for defects is 99.5%, highlighting the model's outstanding capability in accurately detecting and localizing defect spots. Overall, these results underscore the YOLOv5x model's exceptional accuracy and reliability in detecting and localizing various classes within solar panel images.

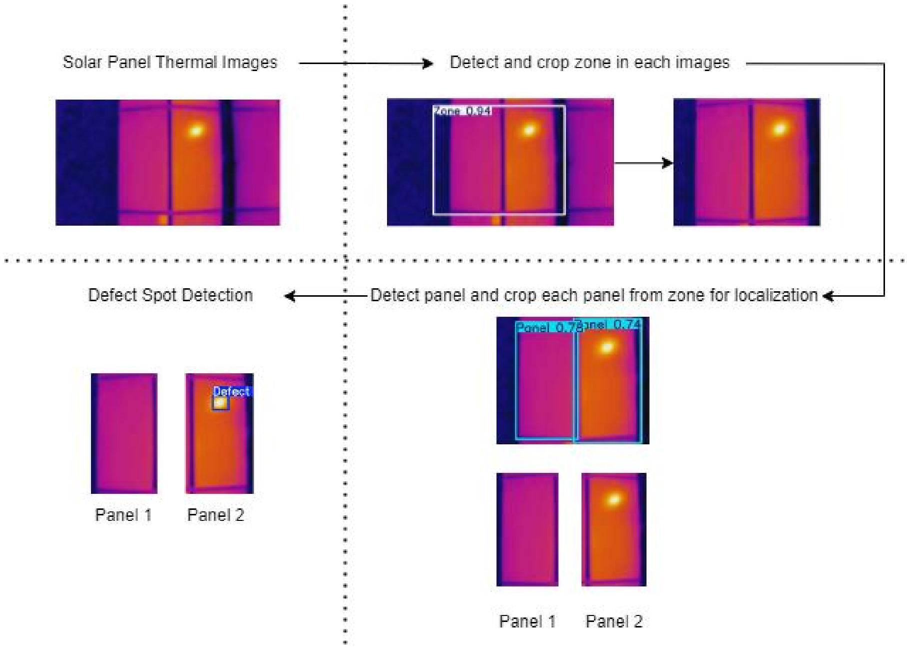

Fig. 4. Detection Process

4.2 Detection Results

Based on Figure 4, a thermal solar image is presented, containing a zone. The zone in this image was successfully detected, with a 94% confidence level. This high confidence level indicates that the model is highly certain about the presence and correct identification of the zone within the thermal image.

Once the zone is identified, the next step involves cropping this zone to isolate the panels within it. During this stage, two panels are detected in total. The detection confidence for these panels varies. The first panel is detected with a confidence level of 78%, and the second panel is detected with a confidence level of 74%, both of which are considered reliable for practical applications.

The detected panels are then labelled sequentially, with the first detected panel labelled as panel 1 and the second as panel 2. This sequential labelling aids in organizing and tracking the panels during subsequent analysis, effectively achieving localization.

Finally, the model proceeds to detect defect spots within the identified panels. One defect spot is detected, located in panel 2, with an 82% confidence level. This high confidence level for defect detection indicates that the model is quite reliable in identifying defects within the panels.

In summary, our proposed approach has effectively localized each panel within the thermal images and accurately detected the defective spots. The high confidence levels in the detections demonstrate the robustness and reliability of the model. This approach ensures that solar panels and their defects can be monitored and maintained efficiently, contributing to better management and optimization of solar energy systems.

5 Conclusion

In conclusion, our approach using the YOLOv5 model has proven highly effective in detecting defects and localizing solar panels. The model successfully classified zones, cropped and localized panels, and identified defect spots with near-perfect accuracy. The final training results demonstrate exceptional performance, with a precision of 94.7%, recall of 96.8%, and mAP50 of 98.9% across all classes. Our method was validated through the analysis of thermal solar images, where it accurately detected zones, localized panels, and identified defects with high confidence. This robust performance highlights the potential of our approach for improving solar panel maintenance and efficiency.

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References

[1] A. O. M. Maka and J. M. Alabid, "Solar energy technology and its roles in sustainable development," *Clean Energy*, vol. 6, no. 3, pp. 476–483, 2022, doi: 10.1093/ce/zkac023.

[2] A. Sharif, M. S. Meo, M. A. F. Chowdhury, and K. Sohag, "Role of solar energy in reducing ecological footprints: An empirical analysis," *J. Clean. Prod.*, vol. 292, p. 126028, 2021, doi: 10.1016/j.jclepro.2021.126028.

[3] M. Vaka, R. Walvekar, A. K. Rasheed, and M. Khalid, "A review on Malaysia's solar energy pathway towards carbon-neutral Malaysia beyond Covid'19 pandemic," *J.*

Clean. Prod., vol. 273, p. 122834, 2020, doi: 10.1016/j.jclepro.2020.122834.

[4] A. Dhoke, R. Sharma, and T. K. Saha, "A technique for fault detection, identification and location in solar photovoltaic systems," *Sol. Energy*, vol. 206, no. February, pp. 864–874, 2020, doi: 10.1016/j.solener.2020.06.019.

[5] U. Hijjawi, S. Lakshminarayana, T. Xu, G. Piero, and M. Fierro, "A review of automated solar photovoltaic defect detection systems : Approaches , challenges , and future orientations," *Sol. Energy*, vol. 266, no. October, p. 112186, 2023, doi: 10.1016/j.solener.2023.112186.

[6] S. P. Pathak, D. S. Patil, and S. Patel, "Solar panel hotspot localization and fault classification using deep learning approach," *Procedia Comput. Sci.*, vol. 204, pp. 698–705, 2022, doi: 10.1016/j.procs.2022.08.084.

[7] H. Cao, H. Zhang, C. Gu, Y. Zhou, and X. He, "Fault detection and classification in solar based distribution systems in the presence of deep learning and social spider method," *Sol. Energy*, vol. 262, no. March, p. 111868, 2023, doi: 10.1016/j.solener.2023.111868.

[8] Ultralytics, "YOLOv5: A state-of-the-art real-time object detection system." 2021. [Online]. Available: https://docs.ultralytics.com

[9] M. Du, "Machine vs. human, who makes a better judgment on innovation? Take GPT-4 for example," *Front. Artif. Intell.*, vol. 6, 2023, doi: 10.3389/frai.2023.1206516.

[10] J. Huang, K. Zeng, Z. Zhang, and W. Zhong, "Solar panel defect detection design based on YOLO v5 algorithm," *Heliyon*, vol. 9, no. 8, p. e18826, 2023, doi: 10.1016/j.heliyon.2023.e18826.

[11] M. Zhang and L. Yin, "Solar Cell Surface Defect Detection Based on Improved YOLO v5," *IEEE Access*, vol. 10, no. August, pp. 80804–80815, 2022, doi: 10.1109/ACCESS.2022.3195901.

[12] M. Y. Iqbal Basheer *et al.*, "Autonomous anomaly detection for streaming data," *Knowledge-Based Syst.*, vol. 284, no. December 2022, p. 111235, 2024, doi: 10.1016/j.knosys.2023.111235.