

# Drone-based solar panel inspection using machine learning

*Jiten Praburam, and Mohammed Afzel, Balachandar Krishnamurthy* \*

School of Mechanical Engineering, Sathyabama Institute of Science and Technology, Chennai 600119, India.

**Abstract.:** The paper represents the experimental implementation of a Drone-based solar panel inspection using YOLOv8-based object detection with Ultraviolet sensing for automated and enhanced defect inspection. A quadcopter platform was equipped with imaging sensors that was used to capture aerial images of the solar panels. The dataset used consists of 1500 annotated images categorized into clean panels, surface cracks, dust accumulation and thermal defects. The YOLOv8 model was fine-tuned using the dataset which had an input of 500x500 resolution for training a series of 100 epochs. Transfer learning enabled object localization and classification and RGB-based detection, for effective detection and identification of abnormal surfaces, discharge related anomalies where identified successfully that cannot be identified through standard imaging. Experimental validation also demonstrated reliable detection across all categories of defects and the results validated the completion of the project using lightweight deep learning model for object detection with multiple sensor UAV platform for cost-effective inspection, making a cost-efficient and automated solar farm monitoring possible and much more efficient than traditional methods.

Keywords: Solar Panel inspection, YOLOv8, Object detection, Solar Panel Monitoring

## 1 Introduction

The rapid growth in the installations of solar photovoltaic (PV) has increased the need for reliable and efficient inspection methods. Cracks, dust accumulation and thermal hotspots are some of the defects that significantly reduce the efficiency and performance of the panels [4], [5]. A traditional inspection method, like manual surveying, is labor-intensive, time-consuming and is considered less suitable when it comes to large-scale solar farms. UAVs have been adopted widely due to their ability to cover large areas quickly and overcome the limitations of manual surveying while also reducing human effort significantly [1], [2].

---

\*Corresponding Author: [balachandar3089@gmail.com](mailto:balachandar3089@gmail.com)

UAVs equipped with visual and thermal cameras capture high-resolution data that helps in identifying defects that are present in both surface-level and temperature-related defects [7], [9]. Deep learning techniques have improved the inspection methods by automating detection of defects using image data in recent years. Object detection and identification model such as YOLO have shown positive results in detecting different type of defects efficiently [10].

However, existing inspection systems mainly focus on thermal and visual analysis, while giving less or no attention to electrical discharge-related faults. This work proposes a UAV based inspection system that integrates ultraviolet detection with thermal and visual imaging to provide a more efficient and cost-effective solution.

## **2 Literature survey**

### **2.1 UAV-Based Thermal and Visual Imaging for Solar Panel Inspection**

Unmanned Aerial Vehicles (UAVs) are being used for solar panel inspection because of their ability to monitor large areas and reduce manual effort [1], [2]. Making them suitable for large-scale farms where traditional methods are difficult to implement. Thermal imaging is used to detect defects such as hotspots in PV panels. However, it can be affected due to environmental and calibration related issues [4]. Several studies have combined both thermal and visual imaging to improve detection performances. With the help of deep learning, UAV-captured images are being processed automatically for detecting different types of defects and improving both speed and reliability during inspection [7],[9].

### **2.2 Datasets and Benchmarks of PV fault detection**

Machine learning based inspection rely on dataset that are of high-quality for accurate performance. Datasets that were available publicly containing thermal and visual images have supported the development of defect detection models . However, the quality of the images acquired can vary due to motion blur, lighting, and environmental factors. These issues can affect the accuracy of detection [5]. Radiometric thermal imaging have been widely explored in recent studies to improve temperature measurement accuracy, helping in better fault analysis [6].

### **2.3 Deep Learning and Fault Detection Models**

Deep learning has improved automated inspection in PV systems significantly with the help of models likes YOLO which are widely used for defect detecting in UAV- captured images [10]. The models help in the defect detection process more efficiently and supports automated analysis. Techniques such as monitored learning have been applied to improve the representation and classification of collected data [7]. Studies have compared different YOLO-based models, showcasing improvements in detection and processing speed in PV inspection task . Challenges such as latency, scalability and limitations of datasets still affect the performance despite all these advancements [8].

#### *2.4 Autonomous inspection, tracking, advanced sensing with alternative platforms and extended anomalies.*

Development of autonomous UAV-based inspection systems reduced manual efforts and improve efficiency of inspection. Advanced control and navigation methods make effective coverage of inspection possible [8]. Various imaging techniques have been explored to improve the detection process including thermal and visual imaging, which allow identification of different types of faults under varying conditions [2], [11]. Combining multiple techniques has improved detection capability and provides more reliable inspection [2]. However, full autonomy remains challenging due to the limitations in real time processing and data interpretation [3].

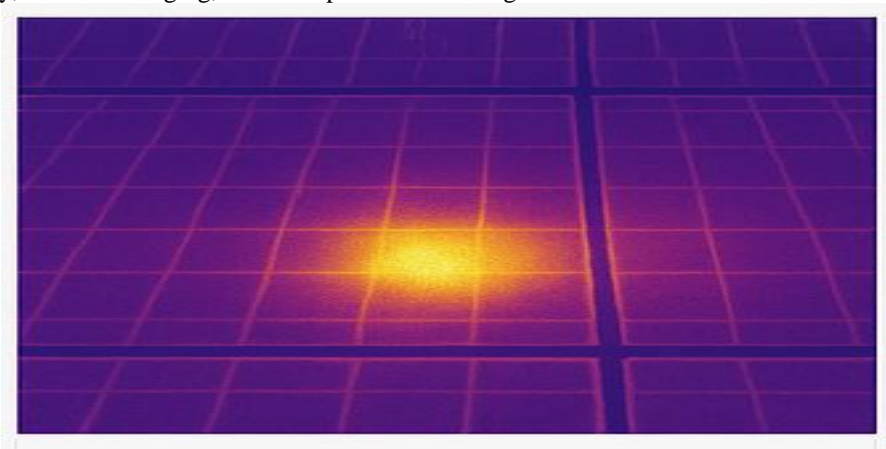
#### *2.5 Multidisciplinary perspective, Fault detection & diagnosis in UAV systems.*

Photovoltaic inspection systems have combined UAV platforms with advanced imaging and machine learning techniques, enabling data collection and automated analysis [1], [11]. Integration of thermal and visual imaging improves fault detection by providing information about the conditions of panel [9]. Inspection process have been enhanced by using automated and consistent defect detection, reducing the need for the manual analysis due to the usage of machine learning models [8], [10]. Environmental variations and data quality still affect the performance and require further improvements [5].

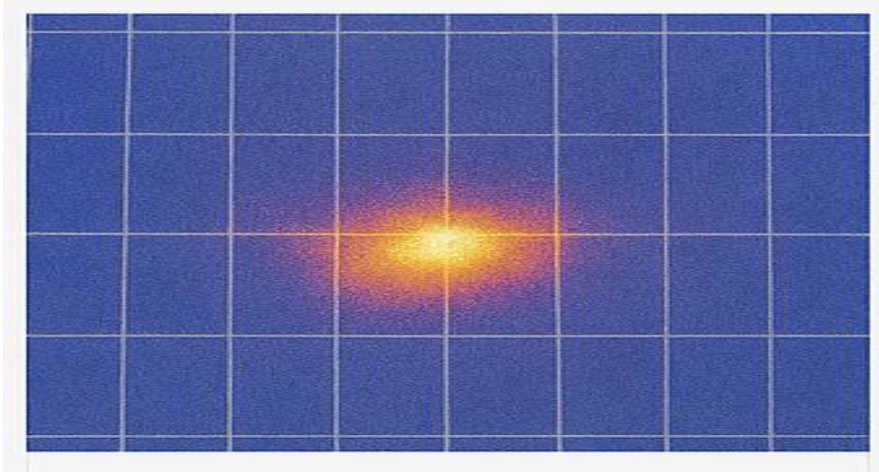
### **3 Types of Defects Found in Solar Panels or PV Panels**

#### *3.1 Hotspots*

These are defects that occur when certain cells operate at a higher resistance, which is mostly due to shading, dust accumulation. Some of the other reasons are overheating, manufacturing defects, and also bypass diode failure, which are caused by the aging of cells. These are sometimes localized to a single cell or appear in a string pattern due to the use of open diodes or failed diodes. Over time, hotspots are a major cause for reduction in efficiency, accelerated aging, and even permanent damage if left unnoticed.



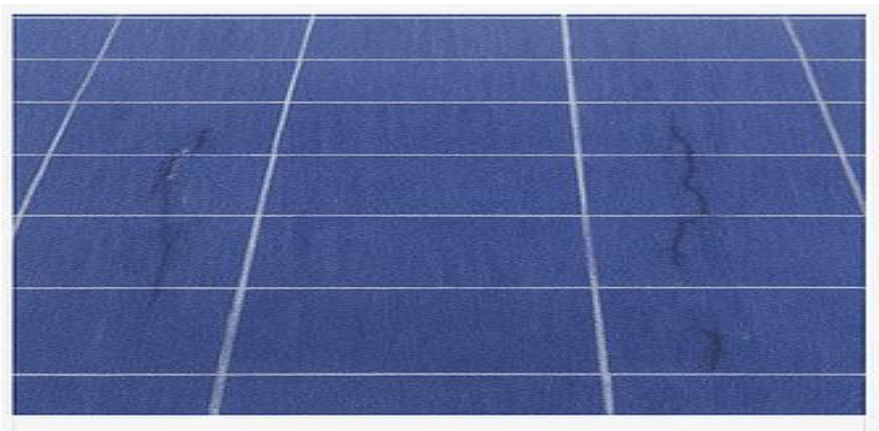
**Fig. 1.** Hotspots



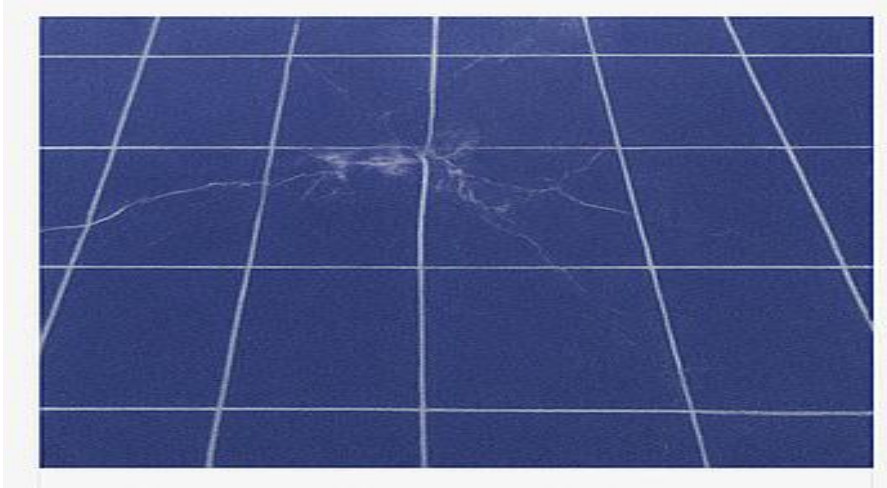
**Fig. 2.** Bypass diodes

### 3.2 *Cracks or Glass Breakage*

Cracks or Glass Breakage mainly occur due to mechanical stress, due to installation, transportation, or environmental impacts like thermal expansion cycles, hailstorms, etc. A crack or glass Breakage leads to a reduction in current flow, a mismatch in power generation, and accelerated internal damage. These mostly show as dark, broken patterns when seen under a visual camera like ESP32-CAM or as fractures or chip formation when seen as RGB images.



**Fig. 3.** Cracks on the surface



**Fig. 4.** Glass Breakage

### 3.3 *Discoloration and Delamination*

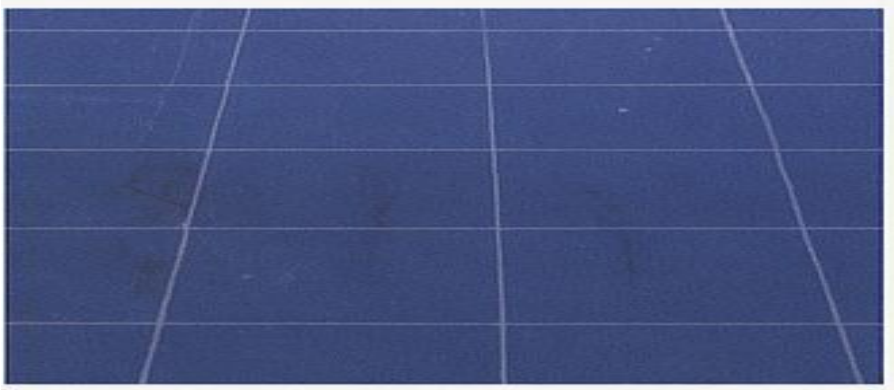
The type of defects that are caused in the encapsulant layer. Over time, the encapsulant layer goes through UV degradation, thermal stress, poor lamination during installation, and moisture ingress, which leads to a discoloration process that often appears as a yellow or brown layer and separation of glass or backsheet, leading to bubble formation or air gaps between the layers of the panels. Often found through Drone visual inspection by usage of normal cameras.



**Fig. 5.** Decoloration

### 3.4 *Snail Trails*

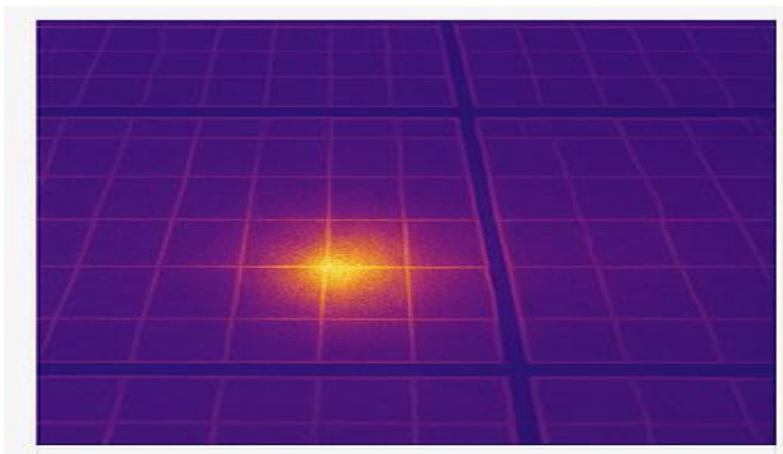
Snail Trails often appear as an irregular dark streak across the surface of the panel most common causes of snail trails are moisture content present or chemical reactions that happen in the encapsulant layer. Mostly drone RGB imaging is used to find these irregular dark discoloration lines, which lead to efficiency reduction and degradation of panels that is localized to particular parts.



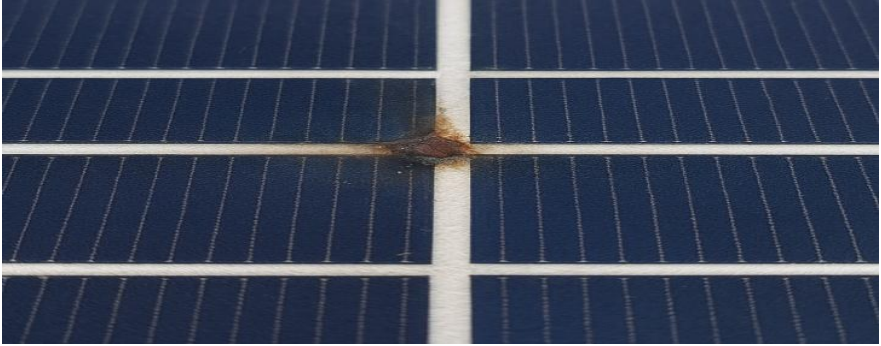
**Fig. 6.** Snail Trails

### 3.5 *Loose Connections and Solder Joint Failure*

These are defects that appear in the form of hotspots that appear only on certain parts or cells, which are caused due to poor installations, corrosion due to environmental impacts, or aging. These defects are identified using drones by thermal imaging and looking for hotspots near connectors, while dangling cables, which risk arching and power loss, can be identified by normal cameras. Another type of defect is solder joint failure, this defect happens when the soldered connection between the cells or busbars gets weakened. This increases the resistance, which leads to inconsistent current flow and, like a loose connection, causes hotspots near connector joints. They are often shown as burnt spots near the connectors, while they also appear as hotspots when seen through a thermal camera.



**Fig. 7.** Loose Connections



**Fig. 8.** Solder Joint Failure

### *3.6 Corona Discharge and Potential Induced Degradation (PID)*

Corona discharge most commonly occurs at faulty connectors due to a breakdown in insulation or improper pinching of wires. While PID occurs due to a difference in voltage between cells and the grounded frame. While Corona Discharge defects produce sparks, noise, or emit ozone gas, PID defects can lead to uneven heating and power loss, which can lead to major issues if left unnoticed. With a UV camera-mounted drone, the bright glowing sparks or regions due to corona discharge can be found and PID defects can sometimes appear as thermal anomalies, which require a thermal camera, a UV camera, as sometimes they give out discharges too, or even appear as patches of reduced performance depending on the severity of PID defect.



**Fig. 9.** Corona Discharge

## 4 Methodology

### 4.1 Acquiring Data

On-board sensors, like thermal Camera (MLX90640) and visual camera (ESP32) are used for acquiring images. Approximately, 5 sec per solar panel is required for identification of different types of defects found in PV cells of solar panels.

### 4.2 Data processing

The collected data is preprocessed to ensure consistency and suitability for machine learning. This includes removing inconsistent samples and feature scaling to maintain uniformity.

### 4.3 Machine Learning model

A YOLOv8-based deep learning model is used for defect detection in PV panels from the captured images. In addition, a Long Short-Term Memory (LSTM) model is used to analyze patterns and estimate the performance.

### 4.4 Data storing and Live transmission

Web-based system is developed for real-time data transmission and storage. The data collected is then transmitted to a remote sever, where it is stored for further analysis

## 5 Design and Development in this project

The project integrates a multi-sensor system consisting of a MLX90640 thermal sensor, an ESP32-CAM for visual imaging, and a custom-built UV sensor for detecting electrical discharge defects. Unlike other inspection systems that rely on thermal or RGB imaging, the proposed system combines multi-sensor methods to improve defect detection. Thermal imaging helps in identifying temperature-related anomalies, while visual imaging helps in identifying surface level defects. The UV sensor enables detection of electrical discharge, providing additional diagnosis. A quadcopter platform with optimized mounts for sensors, battery placement, and wiring is used to implement this system. This ensures stability and reliable data acquisition during flight.

## 6 Calculations

Mass of payload ( $M_p$ ) = 1000g or 1kg

Mass of structural ( $M_s$ ) = 1200g or 1.2kg

Total mass ( $M_{tot}$ ) =  $M_p + M_s = 2200g$  or 2.2kg

Voltage of battery ( $V$ ) = 11.1 V

Discharge capacity of battery ( $C$ ) = 10.0Ah

Total energy capacity of battery ( $T_E$ ) =  $V \times C = 11.1 \times 10.0 = 111Wh$

Usable energy (80% for safety) ( $U_E$ ) =  $T_E \times 0.8 = 111 \times 0.8 = 88.8 V$

Hover power ( $P_H$ ) = 150W/ kg

Electric power required ( $P_{REQ}$ ) =  $P_H \times M_{tot} = 150 \times 2.2 = 330W$

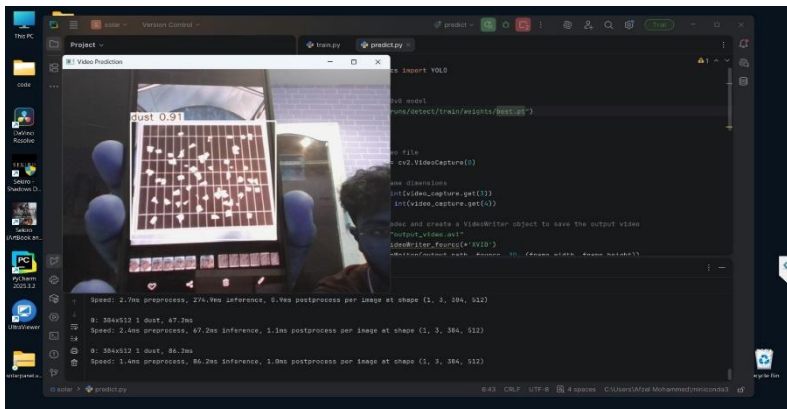
Flight time or Hover time =  $\frac{\text{Usable energy (UE)}}{\text{Electric power required (PREQ)}} = \frac{88.8}{330} = 0.269090\text{hrs}$

Hrs to Minutes =  $0.269090 \times 60 = 16.14\text{mins}$

Hover time is approximately 16.5 mins.

## 7 Results and Findings

The system developed was able to detect defects in PV panels using the implemented deep learning model. Thermal imaging and visual imaging helped in the identification of temperature-related anomalies, and surface level defects. The UV sensor was used to identify the electrical discharge defects. The results indicated that the system can perform multi-sensor equipped inspection in an automated and cost-efficient manner, making it suitable for large-scale farms.



**Fig. 10.** Visual image identification

UV	Temp	Time
34.22 mK/cm2	31.25 C	06-02-2026 14:55:25
34.02 mK/cm2	31.25 C	06-02-2026 14:55:27
34.11 mK/cm2	31.21 C	06-02-2026 14:55:29
34.04 mK/cm2	31.21 C	06-02-2026 14:55:31
34.00 mK/cm2	31.13 C	06-02-2026 14:55:33
34.62 mK/cm2	31.05 C	06-02-2026 14:55:35
35.59 mK/cm2	31.11 C	06-02-2026 14:55:37
33.79 mK/cm2	31.01 C	06-02-2026 14:55:39
31.44 mK/cm2	30.57 C	06-02-2026 14:55:41
32.14 mK/cm2	30.85 C	06-02-2026 14:55:43
32.30 mK/cm2	31.01 C	06-02-2026 14:55:45
32.55 mK/cm2	30.77 C	06-02-2026 14:55:47
32.29 mK/cm2	30.91 C	06-02-2026 14:55:49
32.09 mK/cm2	31.01 C	06-02-2026 14:55:51
32.23 mK/cm2	30.57 C	06-02-2026 14:55:53
32.30 mK/cm2	30.93 C	06-02-2026 14:55:55
32.46 mK/cm2	31.01 C	06-02-2026 14:55:57
32.31 mK/cm2	30.85 C	06-02-2026 14:55:59
32.30 mK/cm2	30.91 C	06-02-2026 14:56:01
32.61 mK/cm2	30.79 C	06-02-2026 14:56:03
32.26 mK/cm2	30.81 C	06-02-2026 14:56:05
33.75 mK/cm2	30.67 C	06-02-2026 14:56:07
32.21 mK/cm2	30.11 C	06-02-2026 14:56:09
32.09 mK/cm2	30.79 C	06-02-2026 14:56:11
31.84 mK/cm2	30.85 C	06-02-2026 14:56:13
32.17 mK/cm2	30.87 C	06-02-2026 14:56:15

**Fig. 11.** Temperature and UV detection

## 8 Challenges Faced and Future Research Directions

UAV-based inspection systems face challenges despite advancements. One of the issues is the quality of images captured during flight, factors such as motion blur, camera angle and environmental condition affect the clarity, which in turn impacts defect detection [5]. Deep learning models used for detection of defects also faced challenges related to dataset limitations like variations in panel types, environmental conditions and data imbalance which lead to reduced model generalization and performance [10]. Although multi-sensor systems improve detection, integrating different modalities increases complexity and processing requirements [11]. Future work should be focusing on improving image quality, developing robust and diverse datasets. Improving system adaptability and enhancing multi-sensor integration can increase the effectiveness of the inspection systems.

## 9 Conclusion

This work presented a cost-efficient and autonomous UAV-based solar panel inspection for improving the inspection in large scale farms. The system also integrates aerial imaging with YOLOv8- based deep learning model to detect defects automatically. The integration of the multi-sensor data improves the reliability of fault detection by capturing, surface level, temperature related anomalies and electrical discharge defects. The results indicate the system can be used to reduce inspection time and manual effort while maintaining consistent performance.

## References

1. A. Al Mamun, F. M. Gonzalez-Longatt, and R. J. Best, "Inspection and fault detection of photovoltaic arrays using UAVs," *Solar Energy*, vol. **196**, pp. 177–189, (2020). <https://doi.org/10.1016/j.solener.2019.11.038>
2. A. Michail *et al.*, "A comprehensive review of UAV-based approaches to support photovoltaic plant diagnosis," *Heliyon*, vol. 10, no. 1, p. e23983, Jan. (2024) <https://doi.org/10.1016/j.heliyon.2024.e24903>
3. J. Aghaei, P. Kosmopoulos, S. C. Livera, and J. A. Tsanakas, "Autonomous monitoring of PV systems : A multidisciplinary review on UAVs, AI, and future perspectives," *Prog. Photovolt.*, vol. 33, no. 1, pp. 45–70, (2025). <https://doi.org/10.1002/pip.3724>
4. J. A. Tsanakas, L. Ha, and C. Buerhop, "Faults and infrared thermographic diagnosis in operating c-Si photovoltaic modules : A review of research and future challenges," *Renew. Sustain Energy Rev*, vol. **62**, pp. 695–709, (2016). <https://doi.org/10.1016/j.rser.2016.04.079>
5. T. A. Solend, A. Rødningsby, and H. J. F. Moen, "Impacts of infrared thermographic image blurring on UAV inspection efficiency of solar power plants," *Solar Energy*, vol. **299**, p. 113673, (2025). <https://doi.org/10.1016/j.solener.2024.113673>
6. A. E. Alnajjar, D. Issa, A. Khdaif, and S. Altarazi, "Radiometric infrared thermography of solar photovoltaic systems: Toward explainable intelligent inspection," *Electronics*, vol. **14**, no. 4, p. 755, (2025). <https://doi.org/10.3390/electronics14040755>
7. H. Bommers, F. Gaede, and J. Paetzold, "Thermographic inspection of PV modules using UAVs and deep learning for automated fault classification," *Energies*, vol. **14**, no. 4, pp. 1178–1195, (2021). <https://doi.org/10.3390/en14041178>
8. J. Rodríguez-Vázquez *et al.*, "Real-time object detection for autonomous solar farm inspection via UAVs," *Sensors*, vol. 24, no. 3, p. 777, Jan(2024) <https://doi.org/10.3390/s24030777>
9. A. K. Pruthviraj, Y. Kashyap, E. Baxevanaki, and P. Kosmopoulos, "Solar photovoltaic hotspot inspection using UAV thermal images at a solar field in South India," *Remote Sensing*, vol. **15**, no. 7, p. 1914, (2023). <https://doi.org/10.3390/rs15071914>

10. R. Zhang, K. Xu, Y. Liu, and H. Zhao, “YOLOv5-based defect detection in UAV thermal/RGB imagery for PV modules,” *Energies*, **vol. 15**, no. 22, p. 8579, (2022). <https://doi.org/10.3390/en15228579>
11. A. de Oliveira, M. Vallim, R. Villan, L. O. Seman, and F. Silva, “Automatic inspection of photovoltaic plants using aerial infrared thermography: A review,” *Energies*, vol. 15, no. 19, p. 7032, (2022). <https://doi.org/10.3390/en15197032>