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Research article

Detection and analysis of deteriorated areas in solar PV modules using unsupervised sensing algorithms and 3D augmented reality

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ABSTRACT

Solar Photovoltaic (PV) systems are increasingly vital for enhancing energy security worldwide. However, their efficiency and power output can be significantly reduced by hotspots and snail trails, predominantly caused by cracks in PV modules. This article introduces a novel methodology for the automatic segmentation and analysis of such anomalies, utilizing unsupervised sensing algorithms coupled with 3D Augmented Reality (AR) for enhanced visualization. The methodology outperforms existing segmentation techniques, including Weka and the Meta Segment Anything Model (SAM), as demonstrated through computer simulations. These simulations were conducted using the Cali-Thermal Solar Panels and Solar Panel Infrared Image Datasets, with evaluation metrics such as the Jaccard Index, Dice Coefficient, Precision, and Recall, achieving scores of 0.76, 0.82, 0.90, 0.99, and 0.76, respectively. By integrating drone technology, the proposed approach aims to revolutionize PV maintenance by facilitating real-time, automated solar panel detection. This advancement promises substantial cost reductions, heightened energy production, and improved performance of solar PV installations. Furthermore, the innovative integration of unsupervised sensing algorithms with 3D AR visualization opens new avenues for future research and development in the field of solar PV maintenance.

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1. Introduction

The generation of energy, particularly from fossil fuels, leads to the release of greenhouse gases such as carbon dioxide (CO2) into the atmosphere [1]. These emissions contribute to global warming and climate change. By saving energy, we can decrease the demand for fossil fuel-based energy production, leading to lower greenhouse gas emissions and a reduced impact on the environment [2].

Renewable energy, especially solar power, has emerged as a prominent solution in addressing global concerns related to climate change, unpredictable weather patterns, and the finite nature of fossil fuel resources [3,4]. This has led to a significant increase in the deployment of photovoltaic (PV) power stations on a global scale [5].

In light of the global advancements in renewable energy technologies enhancing the competitiveness of solar and wind energy, renewable energy transcends economic benefits, becoming an imperative solution to the prolonged energy crisis [6].

In paper [7], the authors offer a comprehensive analysis of solar energy potentials, employing the System Advisor Model (SAM) to suggest solar photovoltaic solutions designed to alleviate persistent energy challenges. In [8], the authors present an optimization strategy for integrating Pumped Hydroelectric Storage with a hybrid solar-wind system, utilizing the SAM to bolster sustainable electricity supply in urban areas. The study in [9] provides a comparative assessment of various solar energy conversion systems, applying the SAM to identify efficient solar technologies suitable for utility-scale applications. Solar power (SP) offers numerous advantages over traditional energy sources. Firstly, it is a clean and sustainable energy option, emitting minimal greenhouse gases during electricity generation. By harnessing sunlight, solar panels convert this abundant resource into usable electricity, reducing reliance on non-renewable fossil fuels and mitigating the environmental impact associated with their extraction and combustion [10]. Additionally, SP installations have become more economically viable in recent years. Advancements in PV technology, coupled with declining costs, have made solar energy increasingly affordable and competitive with conventional energy sources. As a result, governments, businesses, and homeowners are investing in solar power systems to reduce energy costs, achieve energy independence, and contribute to a greener future [11].

The global trend toward SP adoption has been driven by various factors. Moreover, government policies and incentives, such as feed-in tariffs and tax credits, have encouraged the adoption of solar power systems by providing financial support and favorable regulatory frameworks [11].

As a consequence of these developments, the installation of PV power stations has witnessed a remarkable surge across the globe. Solar farms and large-scale PV installations are being constructed to meet the growing demand for clean energy. This expansion not only facilitates the transition towards a low-carbon economy but also stimulates job creation and local economic growth [12]. In addition to their widespread use, PV modules hold a pivotal role in determining the overall efficiency of a solar power station. However, over time, these modules are prone to a range of defects that can significantly impact their power output efficiency [13]. Ideally, all the PV cells within a string should possess similar electrical characteristics and operate at the maximum power point (MPP) current, thereby optimizing their individual performance.

Unfortunately, variations in the electrical characteristics of the PV cells can occur, resulting in a mismatch in the string current. This mismatch prevents the entire string from operating at each cell MPP, leading to a suboptimal performance [14,15]. One common factor contributing to the reduced efficiency of PV modules is the phenomenon known as Potential-Induced Degradation (PID). PID occurs when the PV module is exposed to high voltage differentials between its conductive elements and the ground. This can lead to leakage currents and subsequent degradation of the module electrical properties, resulting in reduced power output [16]. Other factors that can affect the performance of PV modules include module soiling, shading, degradation of the anti-reflective coating, and hotspots caused by localized heating. Each of these issues can impact the overall efficiency of the SP station and lead to suboptimal energy generation [17,18].

On the other hand, there are several factors that can cause variations in the electrical characteristics of PV modules, such as partial shading [19] and short-circuited bypass diodes [20]. When a low-current PV cell is present in a string of high short-circuit current PV cells, the forward bias across all the cells can reverse bias the shaded cell. This, in turn, significantly increases the temperature of the affected cell, leading to a phenomenon known as hot spotting. Hot spotting can not only damage the cell but also diminish the overall power output of the solar panel [21]. Therefore, conducting regular inspections of PV modules is crucial to ensuring optimal output efficiency.

Moreover, several types of losses that can occur in solar cell fields, which are areas where solar cells are installed to generate electricity from sunlight. These losses can affect the overall efficiency and output of the solar power systems. The types of losses that can be discussed include:

- Shadow Losses [22], shadows cast on solar collectors can significantly reduce their output power capability. This is critical for photovoltaic systems due to mismatch losses.
- Temperature-Related Losses: [23,24] touch on the sensitivity of PV systems to surface temperature. As the temperature of the solar cells increases, their efficiency decreases, leading to power output losses.
- Irradiance Degradation: [25] discusses the degradation of solar irradiance along a row of solar panels, leading to a decrease in the energy received by panels that are not in the first row. This can result in uneven power generation and overall losses in a solar field.
- Economic Parameters: [22]also mentions that the results are critically sensitive to economic parameters such as capital cost, fuel cost, interest rate, inflation rate, etc. While these are not direct physical losses, they affect the economic feasibility and thus the perceived ‘loss’ in terms of investment and returns.

- Meteorological Data Uncertainty: The uncertainty in meteorological data can lead to inaccuracies in the prediction of solar energy generation, as mentioned in [22]. This can be considered a loss in the planning and reliability of solar energy systems.

In recent solar photovoltaic (PV) research, significant advancements include a novel fault identification scheme for PV arrays, enhancing fault detection under challenging conditions such as low irradiance [26]. Another study introduced an innovative fault detection method using minimal sensors, surpassing the limitations of traditional AI techniques and improving system safety and efficiency [27]. Additionally, research on PV panel replacement strategies addressed challenges from manufacturing updates and panel availability, analyzing five replacement scenarios to guide optimal decisions for PV system sustainability [28].

Various methods are employed for PV module inspection, including manual inspection, laser detection for pinpointing potential issues with greater accuracy, satellite observations for obtaining a comprehensive view of the entire setup, infrared thermography for detecting anomalies in heat distribution, and electroluminescence imaging for identifying cracks or other defects that may not be visible to the naked eye [29]. These inspection techniques help identify and address any performance issues or potential risks promptly, allowing for timely maintenance and maximizing the overall efficiency and lifespan of the PV system.

Manual inspection is a laborious process, while techniques such as laser detection and electroluminescence imaging are not suitable for large-scale PV power stations. Infrared thermography is widely adopted for inspecting large PV systems due to its ease of use. However, even with infrared thermography, inspecting a large PV system can be time-consuming as each module needs to be individually inspected [30].

Recently, artificial intelligence has been extensively utilized for anomaly and fault detection [31,32]. In the field of Solar PV Modules Build-up, detecting abnormalities using AI, drones, virtual reality, and other technologies has emerged as a prominent research area. For instance, drone-based infrared thermography has gained considerable attention as a promising approach to streamline the inspection process of PV systems. By utilizing drones equipped with infrared cameras, it becomes possible to efficiently capture thermal data of the entire PV system from an aerial perspective [33]. This technology offers several advantages, such as improved accessibility to hard-to-reach areas and the ability to cover large areas quickly. However, despite its potential, many existing approaches in drone-based infrared thermography still face certain limitations. One major drawback is the reliance on manual drone control, which can be physically demanding and time-consuming. Piloting the drone manually requires skilled operators who must navigate the drone precisely to capture thermal images of all PV modules. This process can be challenging, particularly for large-scale installations that encompass numerous modules [34]. Moreover, a significant issue with existing approaches is the lack of precise information about the location of defective panels. While thermal images obtained by drones can identify areas with abnormal temperatures, they often fail to provide accurate localization of the specific panels that require maintenance. As a result, the subsequent identification and repair of defective panels become more complex and time-consuming, leading to additional delays in the maintenance process [35].

Various techniques have been proposed for damage detection on solar panels. In this section, we provide an overview of some existing techniques and highlight their key characteristics. For instance, Alsafasfeh et al. [36] proposed a technique that combines thermal and visual data imagery to detect various faults. They employed the Canny edge detector, Gaussian filter, and histogram equalization along with seed pixels to identify faults. This technique offers real-time monitoring capabilities for PV system operations and can detect various types of faults. However, it does not specifically address dust-related issues. Similarly, Shihavuddin et al. [37] also developed a technique that utilizes thermal and visual data imagery for fault detection. They employed a single trained model capable of detecting different types of damage and provided a new dataset comprising four specific image sets. While this technique shows promise in detecting various types of damage, the use of a single model may reduce sensitivity to different types of damage. Moving forward, Zyout et al. [38] proposed a technique for surface defect detection using online visual images. They employed AlexNet and CNN convolutional neural networks to classify the images. This technique introduces an innovative concept but relies on manual feature extraction during the detection stage. Furthermore, relying on online data collection may limit the capacity of the classification model.

Furthermore, Henry et al. [34] presented a technique that leverages thermal and visual data imagery to detect deteriorated PV panels. They employed color-based segmentation followed by contour detection to identify faults. The approach was extensively evaluated using a large real-world dataset. However, it should be noted that the determination of the root cause of the detected fault still requires manual intervention. In a different approach, Abuqaaud et al. [39] proposed a technique for dust and soil detection using RGB cameras. They employed the Gray Level Co-occurrence Matrix (GLCM) method for image classification. The technique is relatively straightforward to implement, but it does not account for other classes of anomalies such as shadow areas, broken panels, or wet panels. Additionally, Pierdicca et al. [40] presented a technique for anomaly cell detection utilizing a thermal infrared sensor. They employed the Mask R-CNN architecture for image classification. The technique includes a publicly accessible dataset and has been compared to recent works employing deep neural networks. However, there is room for improvement by incorporating real-time electrical data analysis from operating photovoltaic modules using a monitoring infrastructure.

Table 1 provides an overview of the methods utilized between 2018 and 2023 for identifying faults in solar panels. The table outlines the techniques employed, the data sources utilized, the outcomes attained, and the constraints associated with each method.

Segmenting deteriorating areas of a PV system has the advantage of accurately identifying and diagnosing any problems. With the help of AR technology, maintenance workers can quickly locate and evaluate damaged regions in real time. This means that inspections take less time and repairs can be done faster, resulting in less downtime. AR can also be useful during maintenance and repairs by providing workers with step-by-step instructions on how to fix issues. By superimposing repair instructions and schematics onto the AR display, maintenance workers can reduce the likelihood of making mistakes and improve the quality of repairs [5].

Table 1
Summary of methods used for SP fault detection.

Work Year	Methods	Data Collection	Obtained Results	Limitations
[36] 2018	Real-time inspection system, Thermal and CCD cameras mounted on a drone	Thermal and CCD videos captured by cameras on a drone flying over PV modules	–	Relies on camera-based detection, may be affected by weather conditions and visibility. Limited to faults detectable through visual analysis.
[41] 2020	Two segmentation techniques for photovoltaic (PV) solar panels: filtering by area and active contours level-set method (ACM LS). Refinement using morphological operations and Hough transform	Solar Panel Infrared Image Datasets	Dice = 0.97, IoU = 0.94	Small statistical differences between AF and ACM LS segmentation. Limited to photovoltaic system analysis by cell.
[34] 2020	Autonomous drone-based solution, RGB and thermal cameras, Automatic flight path planning algorithm, Image processing algorithm	RGB and thermal images captured by cameras on a drone flying over PV modules	Automatic detection and localization of faulty PV modules, Precise location estimation	Requires testing and validation for different power plant locations and environmental conditions.
[42] 2020	Thermographic non-destructive tests (TNDTs), Convolutional Neural Network (CNN), Image classification	Thermographic images captured from PV modules, CNN classification	Automatic classification of thermographic images, 98% accuracy in tests	Limited to classification of dust and hotspots. Requires further evaluation for other faults.
[43] 2020	Image processing technique, Maximally Stable Extremal Regions (MSER), Homography translation technique	Thermal and visible images of PV modules	Automatic identification of hot spots, 97% consistency with visual evaluation	Limited to the identification of hot spots and related abnormalities.
[40] 2020	Deep Learning (Mask R-CNN, UNet, FPNet, LinkNet)	UAV-based thermal imaging	0.741 and 0.841 of values on Jaccard and Dice indices	Binary segmentation, Multi-class segmentation, Dataset improvement, Real-time measurements
[37] 2021	Deep learning approach, Unified model, Various modalities (thermal to visual images), Various energy installations	–	Accuracy of 0.79 in surface damage detection	Limited to surface damage detection, specific energy installations considered.
[44] 2022	Drones, Thermal images, MATLAB image analysis, Image acquisition, Grayscale conversion, Filtering, 3D image construction	Solar modules installed on buildings	Improved inspection efficiency, Enhanced defect diagnosis capability	Limited to thermal image-based defects, potential dependency on image quality.
[45] 2023	Ghost Convolution, BottleneckCSP, Tiny target prediction head, YOLOv5, Feature Pyramid Network (FPN), Path Aggregation Network (PAN)	PV panel surface images	Improved accuracy in tiny defect detection, Enhanced model inference speed	Limited to PV panel surface defect detection, potential scalability limitations.

Even though, AR technology can enhance safety during maintenance procedures by visualizing potential hazards and safety issues, it also enables maintenance staff to take necessary precautions and avoid accidents that may cause injury to persons or damage to property, including the PV system. Regardless, despite the growing interest in using AR for various industrial maintenance tasks, there remains a noticeable research gap in exploring the potential of AR for enhancing the maintenance of solar panel PV systems. In addition, AR can decrease the cost of PV system maintenance and repair by facilitating more efficient diagnosis and repair procedures and reducing labor costs and downtime. Moreover, AR provides real-time information on the PV system condition, preventing minor issues from escalating into larger problems, and ultimately extending the system lifespan and decreasing the need for costly repairs. In summary, AR visualization of damaged PV system components offers several advantages, including increased safety, cost savings, and more effective maintenance and repair processes.

To overcome the aforementioned issues, the design, installation, and end-users of photovoltaic (PV) systems can all reap the benefits of augmented reality (AR) visualization. AR offers the potential for a highly realistic and immersive experience of the PV system, which can facilitate adjustments based on real-time usage and enhance the overall efficiency of the system. This, in turn, assists designers and installers in conducting more accurate analyses and making improvements to the system design. Moreover, AR has the potential to enhance users understanding of equipment maintenance and operation, thereby improving their overall experience and proficiency in utilizing the PV system. Additionally, visualization tools improve the localization of deteriorated areas in Solar PV systems by providing enhanced imaging, real-time monitoring, data analysis, augmented reality, 3D modeling, and historical data comparison [46]. Furthermore, the implementation of AR can greatly support PV system installation and maintenance processes [47]. By providing installers with a visual representation of the system in action, AR simplifies the installation and positioning of panels and other components. Additionally, AR technology aids in the identification and diagnosis of any potential issues or maintenance requirements, reducing downtime and optimizing system performance. Overall, the integration of AR in PV systems brings numerous advantages, enhancing the efficiency, effectiveness, and user experience throughout the system lifecycle [48,49].

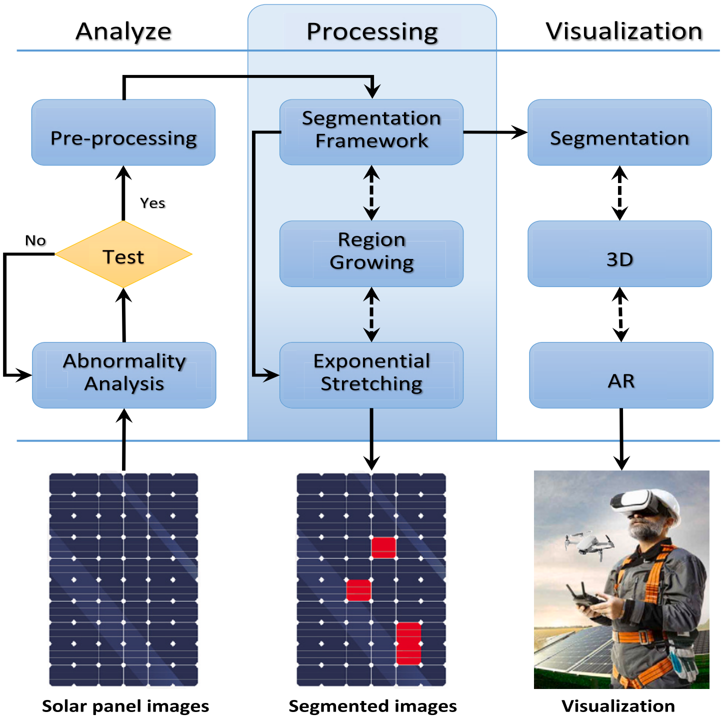


Fig. 1. Block Diagram of the methodology used for analyzing and visualizing deteriorated area in PV module.

Specifically, AR can serve as a powerful tool for promoting the adoption of renewable energy. By providing a delightful and immersive experience [50], AR has the potential to inspire individuals to embrace sustainable energy practices and increase their understanding of PV technology [51]. The utilization of AR in visualizing PV systems offers numerous advantages as it delivers vital information regarding their construction, installation, and maintenance. This, in turn, can contribute to a broader acceptance of renewable energy sources. The combination of augmented reality and infrared thermography presents a comprehensive solution for efficiently monitoring and diagnosing faults in PV modules, thereby enhancing their overall performance and lifespan. By integrating these technologies, the study introduces a novel method for detecting and localizing faults in PV modules utilizing infrared thermography. The proposed method encompasses the following key contributions:

- Evaluating the condition of PV modules to determine if they are functioning normally or if there are any defects present.
- Creating a solution for detecting and locating faults in PV modules by employing improved segmentation techniques and visualizing 3D thermal images sourced from the Cali-Thermal Solar Panels Database.
- Introducing a novel approach for enhancing and segmenting PV images to effectively handle irregularities or anomalies.
- Introducing an advanced system based on Augmented Reality for 3D visualization and localization, which forms an integral part of the proposed method.

The rest of this paper is organized as follows. In Section 1, we delve into a comprehensive literature review on SP fault detection. Section 2 explains our proposed method of abnormality analysis, complete with an insight into data collection and pre-processing strategies. Subsequently, Section 3 showcases the evaluation outcomes and performance comparison of our approach. Ultimately, Section 4 encapsulates the significant findings of the study.

2. Methodology

This section introduces key methodologies for analyzing and visualizing abnormal data in a 3D environment. We cover the abnormality analysis, data collection, pre-processing, 3D broken area tracking using a segmentation framework with exponential stretching function and Region Growing-Based Segmentation, and 3D Augmented Reality visualization and localization. Each technique is essential for the accurate analysis and visualization of abnormality data, and we will delve into their details in the following subsections. Fig. 1 illustrates the block diagram of the methodology used for analyzing and visualizing deteriorated areas in a PV (photovoltaic) module.

2.1. Abnormality analysis method

The Abnormality analysis method is an essential step for saving time before proceeding to segmentation. In our case, we rely on thermal image analysis, referring to the method developed in [34] for detecting abnormal PV modules. This process determines

Table 2
Comparison of Cali-Thermal Solar Panels Image database (Data 1) [52,53] and Solar Panel Infrared Image Database (Data 2) [54].

Category	(Data 1)	(Data 2)
Type of PV Panels	Monocrystalline Si panels, part of a photovoltaic array consisting of 4 serial panels	Specific type not mentioned, total capacity of 42.24 kW, 8 PV strings, 22 PV modules per string
Electrical Characteristics	PV array connected to an electronic equipment emulating a real load	Each PV module rated at 240 W, total system capacity of 42.24 kW
Layout of the Field	PV array of 4 serial monocrystalline Si panels. Data acquired using DJI Matrice 100 drone with Zenmuse XT IR camera	PV system comprised of 8 strings with 22 modules per string. Thermal camera used for data acquisition was handheld and horizontally aligned
Additional Information	Dataset includes 277 thermographic aerial images, temperature, wind speed, and irradiance measurements.	Isolated convolution neural model (ICNM) developed for classifying infrared images of PV panels based on their health and defects. High accuracy and efficiency
images with Anomalies	277	1009 images in three classes
Data Normalization	Cropping	Required; transformation to black and white
Temperature Range	Min = 26 C to Max = 32 C	Min = 2.24 C to Max = 103.33 C
Wind speed	3–5 ms	Not mentioned
Dataset Utilization	Classification of solar panel conditions	Training models for anomaly detection
Fault Detection	Hot spots	Thermal data for any fault detection
Dataset Availability	Public	Public upon request
Equipment/Design	Various equipment including drones and thermal cameras	Skyrobotic SR-SF6 drone with FLIR TAU 2 infrared camera
Data Format/Conditions	Raw thermal images, temperature, irradiance, wind speed, etc.	Raw thermal images, power of 66 MW

PV module health based on different criteria. In this regard, using the thermal image, we determine the highest temperature value T_{max}, lowest temperature value T_{min}, and mean temperature value T_m. Subsequently, either the high-temperature threshold value T_h or the low-temperature threshold value T_l is calculated using either Eq. (1) and Eq. (2), respectively.

$$T_h = T_{mean} + (T_{max} \times 0.2) \tag{1}$$

$$T_l = T_{mean} + (T_{min} \times 0.2) \tag{2}$$

If the temperature value T_{val} is less than T_{max} and T_{min}, the count value a_c is raised. Specifically, the decision rule defined in Eq. (3) is applied to temperature values in the context of analyzing thermal images:

$$f(x) = \begin{cases} a_c + + & if (T_{val} > T_{max}) \text{ or } (T_{val} < T_{min}) \\ a_c & \text{otherwise} \end{cases} \tag{3}$$

Moving forward, the module is classified as abnormal if a_c is greater than 0.2% of the module area value S_{module}, as explained in Eq. (4)

$$g(x) = \begin{cases} \text{abnormal PV module} & \text{if } (a_c > S_{module} \times 0.002) \\ \text{normal PV module} & \text{otherwise} \end{cases} \tag{4}$$

The equation presented above enables the identification of faulty PV modules in a large-scale PV power station. This allows us to focus the subsequent segmentation process specifically on the abnormal PV modules, saving time and resources by narrowing down the analysis to the relevant areas of interest.

2.2. Data collection

Prior to the segmentation and visualization processes, data collection was conducted using the Cali-Thermal Solar Panels Image database [52,53] and Solar Panel Infrared Image Database [54]. This comprehensive datasets include a wide range of test images depicting various areas of solar panel deterioration, as illustrated in Fig. 2(a). These datasets encompasse diverse scenarios of deteriorated cases, encompassing different types of deterioration or sample PV panels. Indeed, Fig. 2 serves also as a visual representation of the differences in visual appearance between abnormal and normal PV modules, providing a visual reference for identifying potential defects in this database.

In Table 2, a comprehensive comparison is presented between two distinct solar panel image databases: the Cali-Thermal Solar Panels Image database (Data 1) and the Solar Panel Infrared Image Database (Data 2) [54]. The comparison spans various categories, including the number of images with anomalies, data normalization procedures, temperature ranges, wind speed conditions, dataset utilization purposes, fault detection methods, dataset availability, equipment and design specifications, data format and conditions, as well as the geographical location of the data collection.

On the other hand, we also picked the dataset solar panel infrared images v5 [55] for segmentation purposes. The dataset includes 934 images of solar panels, which are annotated in Tensorflow Object Detection format. Each image has been resized to a resolution of (416 × 416) pixels. This dataset is designed for computer vision projects related to solar panel inspection and defect detection [56,57]. In Fig. 2(b), representative samples of the dataset are depicted, providing a visual representation of the underlying data.

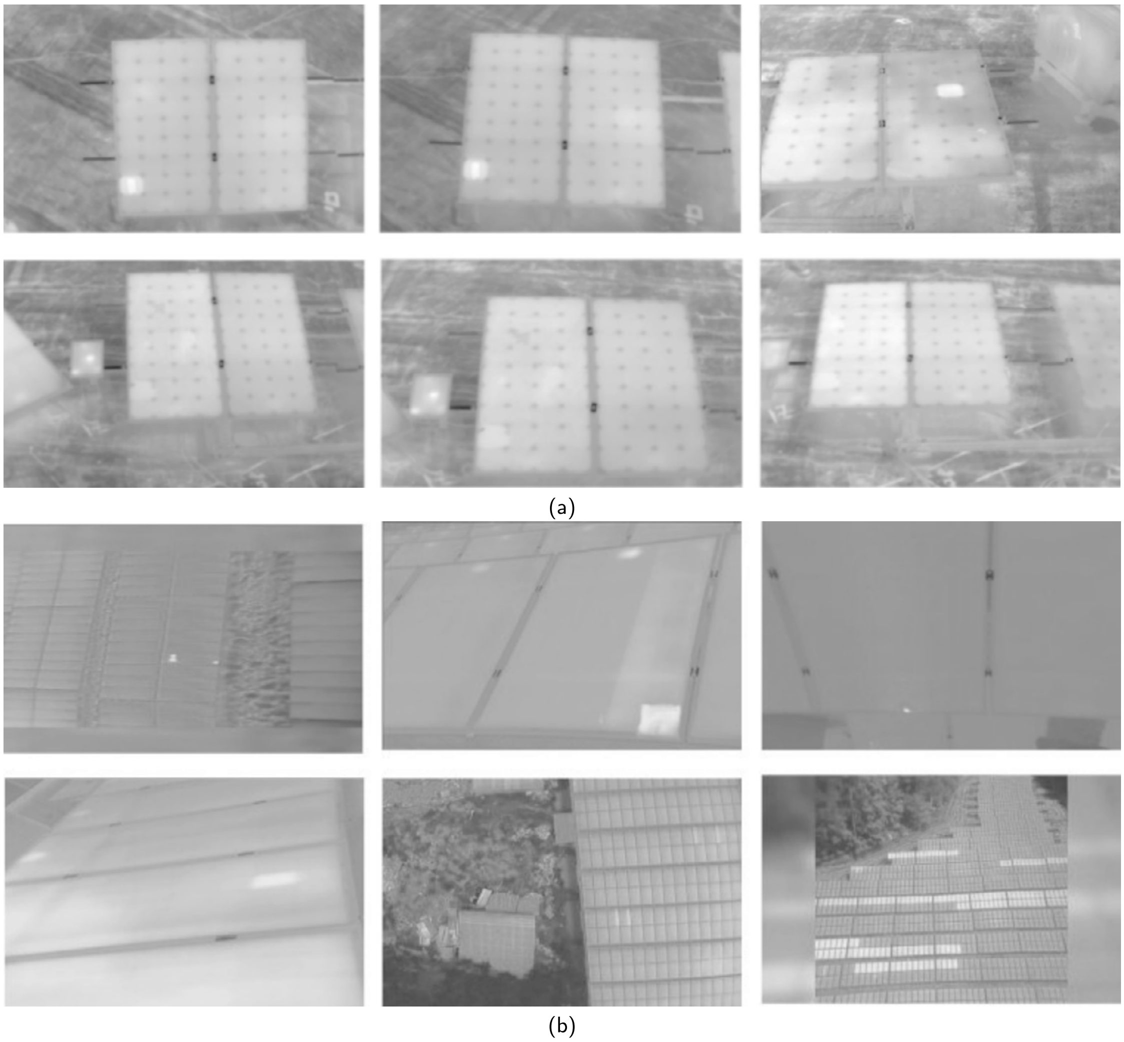


Fig. 2. Samples of abnormal and normal PV modules highlighting the distinct differences in visual appearance and potential defects on (a) Cali-Thermal Solar Panels and (b) Solar Panel Infrared Image Database.

2.3. Segmentation framework for tracking 3D broken areas

The histogram stretching technique plays a crucial role in spatial domain pre-processing methods, which are essential for enhancing images, recognizing patterns, and performing binarization and segmentation. The linear stretching approach is widely employed for expanding luminance levels uniformly. However, its effectiveness is limited when the luminance levels are fully distributed. To overcome this limitation, non-linear techniques are utilized to compress some dynamic luminance levels while expanding others.

2.4. Exponential stretching function

This study introduces an exponential stretching function to expand the bright region. The function is described in Eq. (5):

$$f(x) = x_{L-1} \cdot \left(1 - e^{-\frac{x - x_{min}}{x_{max} - x_{min}}}\right) \tag{5}$$

where x refers to a luminance level, $x_{(L-1)}$ denotes the total number of luminance levels within a permitted range, x_{min} and x_{max} represent the minimum and maximum luminance levels, respectively.

2.5. Region growing-based segmentation

This technique utilizes the region-growing method to combine image pixels, in which the starting point is divided into multiple locations. The algorithm calculates the region of interest into multiple regions and identifies redundancies. Finally, redundant regions are displayed in different colors. Algorithm 1 can be expressed as:

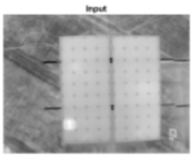
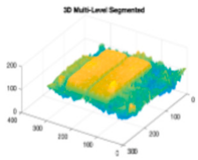
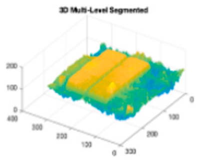
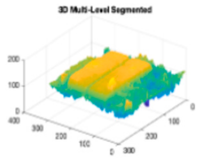
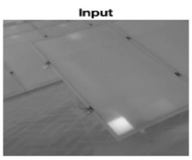
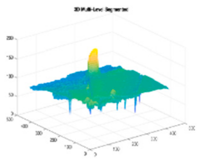
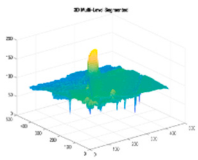
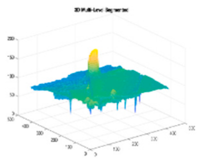
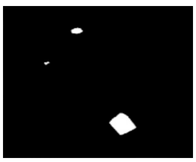
Algorithm 1: Region Growing-Based Segmentation.

Input: Stretched image, $S_{i,j}$
Output: Binary Image, $B_{i,j}$, and Segmented Regions, $C_{i,j}$
Parameter Initialization:
$\epsilon \leftarrow$ a constant: Define the acceptable error within the context of the segmentation procedure, $\epsilon \leftarrow 5$.
$k \leftarrow$ a constant: Define the surrounding pixel, $k = [1, 2, \dots, N]$, $N \leftarrow 4$.
$\tau \leftarrow$ a threshold: Define the image-dependent threshold.
Process:
$p_{i,j} \leftarrow 1$ when $S_{i,j} \geq \tau$
for $a \leftarrow 1$ **to** $i \times j$ **do**
  $R_{a,k} \leftarrow p_a$
  while $\left(\frac{1}{N} \sum_{k=1}^{N} R_{a,k} \right) < \epsilon$ *and size* $< S_{i,j}$ **do**
    $R_{a,k}$ is connected to its surrounding pixels.
  $R_a \leftarrow \bigcup_{k=1}^{N} R_{a,k}$

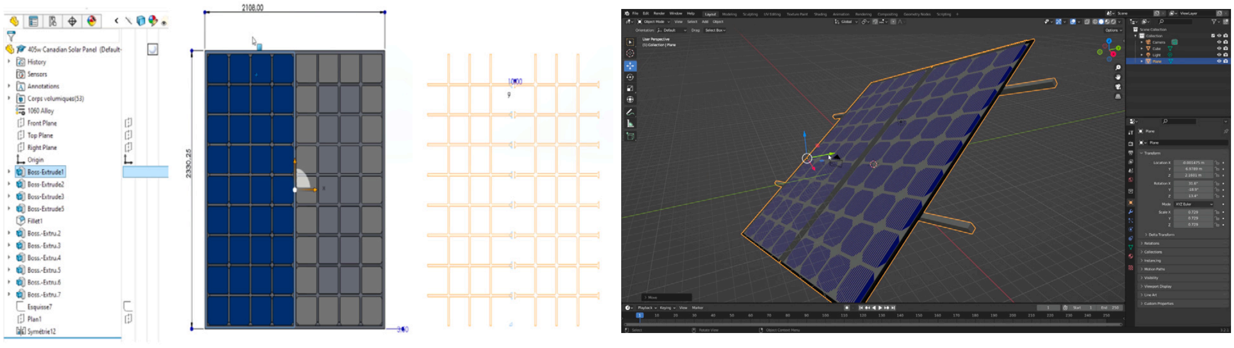
$$B_{i,j} \leftarrow \begin{cases} 1, & \text{when } R_a < \frac{1}{N} \sum_{k=1}^{N} R_{a,k} \\ 0, & \text{otherwise} \end{cases}$$

$R_{i,j} \leftarrow \prod_{a=1}^{i \times j} R_a$
$C_{i,j} \leftarrow R_{i,j} \odot S_{i,j}$ where $\odot$ denotes a dot product operator.

Table 3
Parameters selection.

Image	$\varepsilon = 3, \tau = 160$	$\varepsilon = 5, \tau = 160$	$\varepsilon = 7, \tau = 160$
			
GT		Segmented	
			
Image	$\varepsilon = 3, \tau = 128$	$\varepsilon = 5, \tau = 128$	$\varepsilon = 7, \tau = 128$
			
GT		Segmented	
			

For ε, it is set as 5. The region is iteratively grown by comparing all unallocated neighboring pixels to the region, less than a region-based mean error. Based on Table 3, $\varepsilon = 5$ generates a corresponding segmented image compared with its ground truth. In the case of $\varepsilon = 7$, the segmented regions become larger than its ground truth. For $\varepsilon = 3$, the segmented regions are smaller. As shown in Table 2. For k, it is set as 4 (north, east, west, and south directions). Algorithm 1 describes a general form. For τ, it is an image threshold. If $\tau = 128$ and the threshold is less than 160 (the dataset-dependent threshold), the results show inaccurate segmented regions. The threshold is crucial for classifying pixels with higher illumination. These pixels are initialized as seeds for multi-level segmentation. As shown in Table 3, the lower the value of ε, the more under-segmented the result. When $\varepsilon = 7$, it over-segments and includes unwanted parts.



(a) (b)

Fig. 3. (a) Solidworks conception, (b) PV Blender conception.

2.6. Limitations, assumptions, and uncertainties

The methodology of this research is primarily based on thermal image analysis, which is susceptible to external influences such as ambient conditions, potentially leading to inaccuracies in identifying abnormal PV modules. The segmentation framework may face challenges with minimal or low-contrast deteriorations. We assume that thermal images reliably indicate PV module health and that the regions of interest are homogeneous. However, uncertainties arise from the dependency on the quality of thermal imagery and the precision of temperature measurements, as well as the chosen parameters for the segmentation framework, which could impact the overall reliability of the results.

2.7. 3D augmented reality visualization and localization approach

In order to improve the visualization of PV systems and identify deteriorated areas, we have developed a 3D model of a Solar Photovoltaic panel. The model was created using a combination of SolidWorks [58] and Blender [59] software. Our design process consisted of three main steps: firstly, we created a base for the panel, followed by adding solar cells, and finally, we included details such as mounting holes, rounded edges, fasteners, textures, and colors to achieve a more realistic appearance. This 3D model serves as a valuable tool for studying and analyzing the behavior of PV systems under different conditions, and it can aid in the identification and diagnosis of areas that may require maintenance or repair.

To begin with, we followed a straightforward three-step process in SolidWorks. Firstly, we created a new SolidWorks document. Secondly, we sketched the shape of the solar panel using 2D drawing tools such as lines, circles, and arcs. Finally, we applied features such as extrusions and cuts to convert the 2D sketch into a detailed and accurate 3D model of the solar panel. This process allowed us to easily and precisely manipulate the design and iterate on various options until we achieved the desired outcome. Overall, the use of SolidWorks significantly streamlined our design process, resulting in a highly efficient and effective design (see Fig. 3(a)).

The photorealistic appearance of our PV design was significantly enhanced through the use of Blender [59]. By incorporating a variety of elements such as textures, colors, mounting holes, and softened edges, we were able to bring our concept to life. The resulting 3D model is highly detailed and visually stunning (see Fig. 3(b)). Additionally, Blender versatile rendering features allowed us to experiment with different lighting and shading settings to achieve the best visualization performance.

Compared to using SolidWorks alone, Blender provided us with more flexibility and options for creating a more realistic and detailed PV design. Its ability to produce photorealistic textures and colors allowed us to better envision the final product. Furthermore, the incorporation of mounting holes and softened edges improved the design usability and functionality. Overall, the combination of SolidWorks and Blender provided us with an efficient and effective approach to producing a high-quality PV design.

2.7.1. AR rendering

We utilized Vuforia SDK [60] to enhance the realism and interactivity of our PV design visualization through augmented rendering. This cross-platform SDK provided robust tools for tracking and augmenting virtual objects in the real world. By utilizing markers as 3D features, we were able to precisely track and modify the design in real-time within the physical environment. These markers, specific forms, and images served as standards for scene localization and augmentation to ensure accurate tracking. With Vuforia augmented virtual rendering, we achieved a highly realistic representation of the PV design in situ. This allowed us to better understand how the design would interact with its environment, a crucial consideration for evaluating its performance. Unity3D [61] was used to create the AR environment, as it allows for full access to any item created and can import 3D models (.FBX) necessary for loading our PV 3D model. Our 3D reconstruction of the segmented deteriorated PV areas was also incorporated.

3. Results

To accurately detect and locate deteriorated cells within PV panels, it is essential to conduct an in-depth abnormality analysis. Before proceeding with the segmentation process, an evaluation of the abnormality analysis results must be performed to identify the

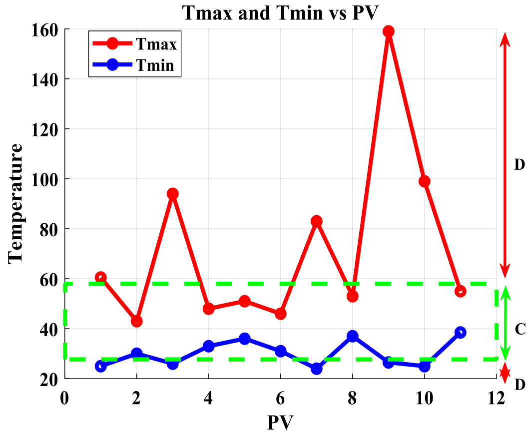


Fig. 4. T_{max} and T_{min} values for 11 PV panels, indicating which panels have deteriorated cells. Segmentation is necessary to accurately delineate the affected region and optimize performance.

specific panels/cells that require further investigation. Once the panels with deteriorated cells are identified, the proposed approach can be segmented and then evaluated using computer simulations to ensure its effectiveness.

Upon evaluation, the next step involves segmenting the PV panels to isolate the regions with deteriorated cells. This process is crucial in accurately identifying the damaged areas and preventing false positives. The segmentation results are then analyzed to obtain a comprehensive understanding of the extent of the damage.

To provide a more intuitive understanding of the damaged regions, AR visualization techniques can be employed. The AR visualization results enable users to visualize the damage in real time, providing a clearer picture of the damage. In brief, in this section, we discuss the abnormality analysis results, evaluation of the proposed approach using computer simulations, segmentation results, and AR visualization results.

3.1. Abnormality analysis results

Fig. 4 illustrates the T_{max} and T_{min} values of 11 PV panels, providing information on their states. The panels with deteriorated cells can be identified by analyzing the obtained values, which is important for selecting the panel to which the segmentation approach will be applied. This can significantly reduce processing time. Panels 2, 4, 5, 6, 8, and 11 exhibit thermal values (T_{val}) within the range $T_{min} < T_{val} < T_{max}$ ($25\,°\mathrm{C} < T_{val} < 40\,°\mathrm{C}$), indicating that these panels are clean and do not require segmentation based on the approach proposed in subsection A. In contrast, panels 1, 3, 7, 9, and 10 display thermal values outside this range ($T_{val} < T_{min}$ and $T_{val} > T_{max}$), indicating deteriorated cells. These panels experience unfavorable operating conditions, such as increased heat stress or reduced efficiency, leading to higher and lower temperature values. The T_{max} values for these panels are higher than those of the other PVs, suggesting that one or several cells have deteriorated. Similarly, the T_{min} values for these panels are lower, indicating that they integrate cells with very low performances. The analysis of Fig. 4 emphasizes the importance of identifying the specific reasons for PV panel performance deterioration and implementing appropriate measures to mitigate the negative effects and optimize performance. Therefore, segmentation is necessary to accurately delineate the affected region.

3.2. Visual inspection results

The segmentation performance of the proposed method, Segment Anything Model (SAM) [62], and Weka approaches was evaluated visually on a set of degraded imagery samples. The evaluation was conducted by comparing the segmented hotspots of the proposed method with those obtained using SAM [63] and Trainable Weka Segmentation [64]. The ground truth was used as a reference to compare the segmentation results, as shown in the second column of Fig. 5.

The segmentation results were compared in terms of visual inspection, and the subjective findings are presented in Fig. 5. The results indicate that the proposed method outperforms the other two approaches in segmenting abnormality regions. Specifically, the proposed method achieves a more accurate and precise segmentation of the hotspots compared to SAM and Weka.

It is worth noting that the SAM approach performs relatively well but still falls short of the proposed method. Meanwhile, Weka tends to over-segment the images, leading to less accurate segmentation results. Overall, the proposed method offers better visual segmentation results, which can potentially improve the accuracy and efficiency of hotspot detection and characterization tasks.

3.3. Evaluation of proposed approach using computer simulations

Several statistical methods are widely used to assess the quality of image segmentation. In this paper, we picked the methods including: Jaccard Index (also known as Intersection over Union or IoU) [65]: This quality measurement calculates the similarity

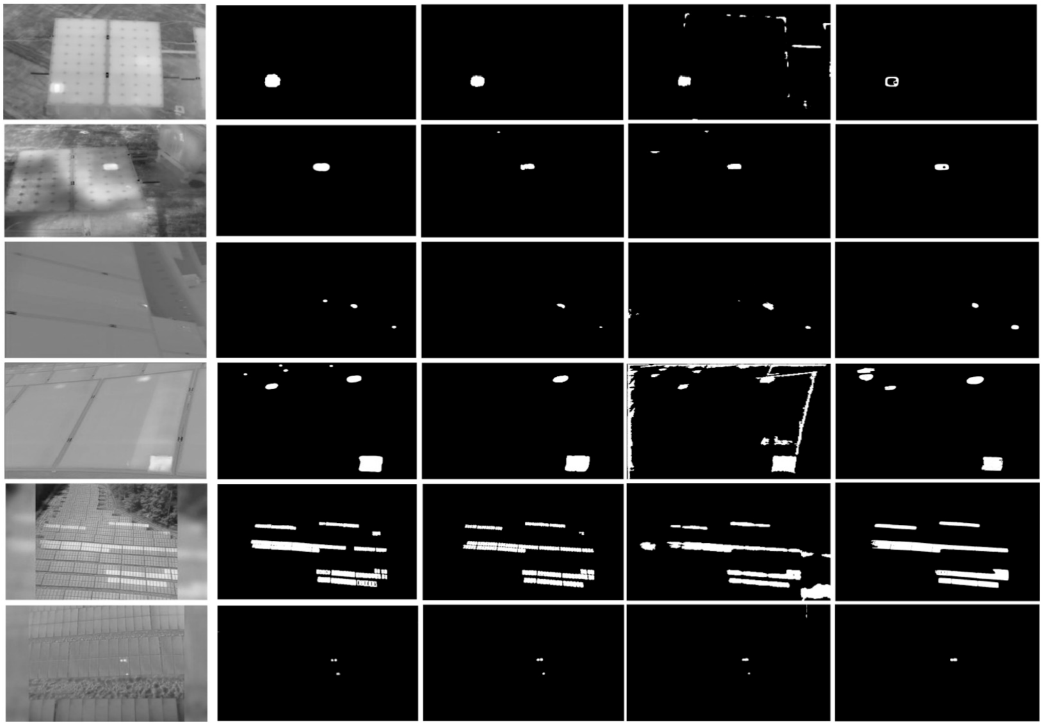


Fig. 5. Visual segmentation comparison of six image examples using various methods: Columns 1–5 respectively show the original image, ground truth, proposed, Weka, and SAM segmentation results.

Table 4
Summary of segmentation metrics used in this study.

Metric	Formula	Description
Jaccard Index (IoU)	$\frac{TP}{TP+FN}$	Measures the similarity between the intersection and union of segmented and ground truth regions.
Dice Coefficient	$\frac{2 \cdot TP}{2 \cdot TP+FP+FN}$	Quantifies the overlap between segmented and ground truth regions.
Precision	$\frac{TP}{TP+FP}$	Evaluates the accuracy of positive predictions among the segmented regions.
Recall (Sensitivity)	$\frac{TP}{TP+FN}$	Measures the ability to detect positive instances in the ground truth.
Rand Index	$\frac{TP+TN}{TP+TN+FP+FN}$	Assesses similarity based on pixel-wise classifications.

between the segmented region and the ground truth area. The formulas for Jaccard Index and other metrics are summarized in Table 4.

3.4. Performance comparison with existing approaches

The performance of the proposed segmentation approach was evaluated using metrics such as Jaccard Index (IoU), Dice coefficient, Precision, and Recall measures. The statistical results of the segmentation on a set of imagery with deterioration. In order to compare the performance of the proposed approach efficiently, we also compared the statistical values of the segmented hotspot with those obtained using the proposed, SAM [63], and Weka [64] methods as shown in Table 5. In this regard, this table presents the data results of the four matrices observations, discussed earlier, with each method having distinct mean values. As shown in the table, the results indicate that the proposed method has the highest mean values, while SAM [63], and Weka [64] methods have slightly lower mean values compared to the proposed method, and Weka has the lowest mean values among the four methods in terms of precision and DSC. These findings suggest that the proposed method likely performs the best among the evaluated methods.

The implementation of the proposed scheme was carried out on a Windows 10 Pro for Workstations with a 3.7 GHz Intel Core i-9 processor and 32 GB of RAM, using the latest MATLAB Version.

3.5. Heat-map chart analysis for determining the visibility of deteriorated areas

After obtaining the 2D segmentation output, additional processing steps are executed to produce a 3D segmentation output suitable for integration into Blender software. Thus, heat-map chart analysis is a practical procedure picked for determining the

Table 5
Statistical segmentation comparison using the proposed against Weka and SAM segmentation methods.

Method		IoU	Dice S C	Precision	Recall	Rand Index
Weka	μ	0.6869	0.5211	0.4921	0.9660	0.6912
	σ	0.1391	0.1943	0.2601	0.0338	0.1324
SAM	μ	0.6212	0.6645	0.7568	0.9791	0.6646
	σ	0.1927	0.1433	0.2072	0.0405	0.1512
Proposed	μ	0.7680	0.8232	0.9045	0.9961	0.7680
	σ	0.1457	0.0895	0.0739	0.0056	0.1457

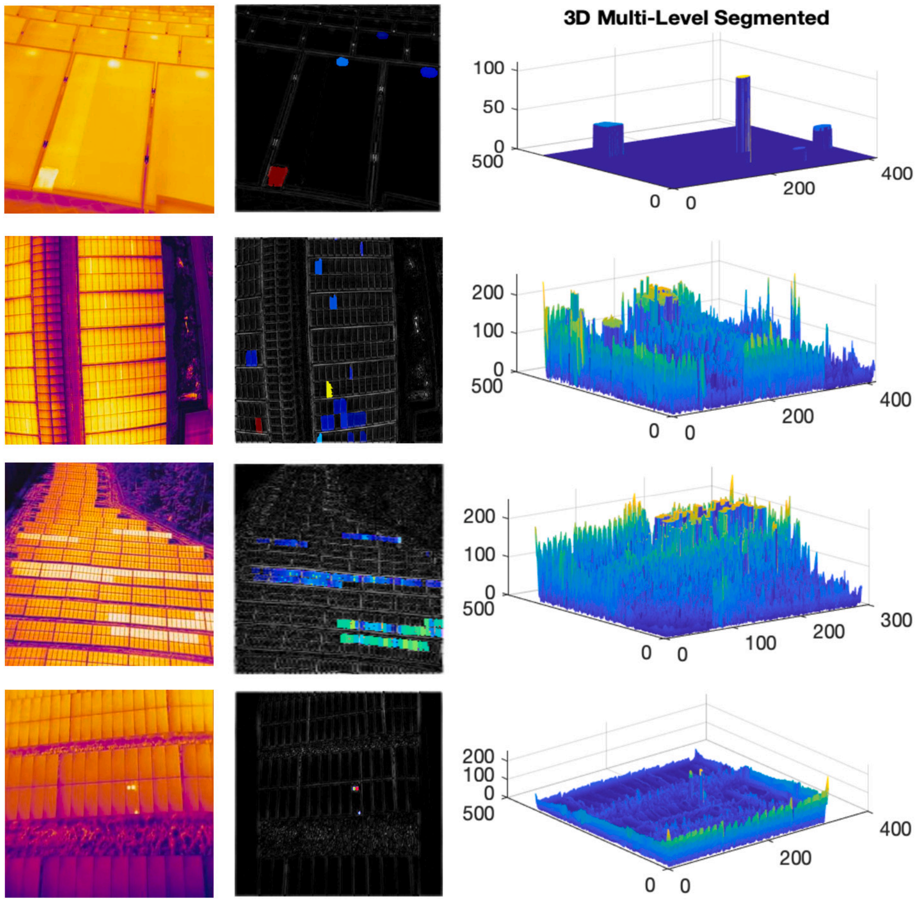


Fig. 6. Heat-map chart analysis of a deteriorated surface of 4 samples. Black areas indicate intact regions, while colored areas indicate higher levels of surface deterioration.

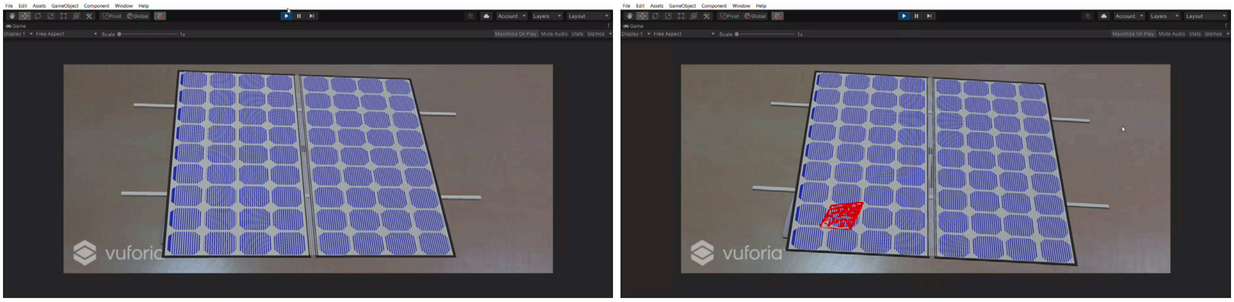
visibility of deteriorated areas. It involves creating a color-coded map that highlights the deteriorated areas of the solar panel with high or low-intensity values. The brighter or warmer colors typically indicate areas of higher intensity, while the darker or cooler colors represent areas of lower intensity.

For example, Fig. 6 shows a heat-map chart analysis of a deteriorated surface. The darker areas in the image indicate intact regions, while the brighter areas indicate relatively higher levels of deterioration surface.

Overall, heat-map chart analysis is a decisive tool for identifying and visualizing areas of deterioration. This technique can be used in conjunction with other image analysis methods to provide a more comprehensive understanding of the extent and severity of deterioration in a given solar panel.

3.6. AR visualization results

Augmented Reality (AR) technology can effectively promote the knowledge and adoption of Photovoltaic (PV) technology and sustainable energy practices by providing an engaging, interactive, and enjoyable experience. The Vuforia SDK for AR rendering



(a) (b)

Fig. 7. PV and AR visualizations: (a) PV Augmented Reality visualization and (b) AR visualization of the PV deteriorated areas.

was used during the design process, providing a robust and user-friendly tool for analyzing and improving the PV design. The AR rendering of PV visualization is depicted in Fig. 7(a), and it can be experienced through smartphones, tablets, and AR glasses.

Segmenting the deteriorated areas of PV systems provides significant benefits in terms of accurately locating and diagnosing issues. AR visualization of these segmented areas enables maintenance personnel to view the PV system and its damaged regions in real time, facilitating precise location and assessment of flaws or damages. Fig. 7(b) showcases the AR rendering of the visualization of the PV deteriorated areas. The utilization of AR technology in PV systems has the potential to revolutionize the way we maintain and optimize our renewable energy sources.

3.7. Discussion

Without seeking input from experts in photovoltaic solar system maintenance, the author independently conducted a visual verification of the virtual augmentation. This decision was guided by several considerations, primarily driven by factors such as the time and cost implications associated with engaging professional users. Furthermore, the author possesses a profound understanding of AR technology and the tools utilized in the verification of visual augmentation, potentially granting deeper insight into how the augmented information aligns with real-world maintenance responsibilities. Following the initial visual verification process, the author plan includes subsequent phases involving expert validation and peer review, aligning with the research objectives and the specific requirements of the solar PV maintenance project. At a later stage, the involvement of external specialists may offer an additional layer of scrutiny and validation for the results. The interpretation and analysis of the results presented in this study demonstrate the effectiveness of the proposed method for detecting and segmenting deteriorated cells in solar PV panels. Fig. 6 provides valuable information on the thermal performance of PV panels, highlighting the need for segmentation to accurately delineate the affected regions. The analysis reveals that panels with thermal values within the range $T_{min} = 25 < T_{val} < T_{max} = 40$ are clean and do not require segmentation, while panels with values outside this range exhibit deteriorated cells.

The segmentation performance of the proposed method was compared with Meta and Weka approaches, and the subjective findings showed that the proposed method outperformed the other two methods in accurately and precisely segmenting abnormality regions. The mean values of the four matrices observations also indicate that the proposed method likely performs the best among the evaluated methods. The heat-map chart analysis proved to be an effective technique for identifying and visualizing areas of deterioration, which can be used in conjunction with other image analysis methods to provide a more comprehensive understanding of the extent and severity of deterioration in a given solar panel.

Furthermore, the study highlights the significance of effective maintenance for solar PV modules. The accurate and efficient detection and segmentation of deteriorated cells can significantly reduce processing time and facilitate the precise location and assessment of flaws or damages, ultimately optimizing the performance of the PV system. Augmented Reality (AR) technology can also play a crucial role in promoting the adoption of Photovoltaic (PV) technology and sustainable energy practices by providing an engaging and interactive experience.

However, this study has limitations that can be addressed in future research. The proposed method was evaluated on a limited set of degraded imagery samples, and more extensive testing is needed to assess its effectiveness on a larger scale. Additionally, the study focused solely on detecting and segmenting deteriorated cells, and future research can explore other aspects of PV maintenance, such as fault detection and diagnosis. Overall, the study offers valuable insights into the importance of effective maintenance for solar PV modules and the potential of advanced technologies like AR in optimizing the performance of renewable energy sources.

4. Conclusion

This paper presents a novel approach for detecting abnormalities, such as hot spots and snail trails, in solar photovoltaic (PV) modules using unsupervised sensing algorithms and 3D augmented reality visualization. By facilitating more effective diagnosis and repair procedures, AR can help to lower the cost of PV system maintenance and repair. The proposed segmentation framework and analysis methods are evaluated using computer simulations and real-world image datasets, demonstrating the effectiveness of the approach in identifying dirty areas in solar PV modules. The findings emphasize the importance of regular maintenance to ensure the efficiency and power capacity of solar PV modules. The short-term aim of this work is to detect solar panels in an automatic and real-time manner using drones, which can significantly improve the efficiency of PV module maintenance. The proposed approach could be a game-changer in the field of solar PV maintenance, as it allows for quick and accurate detection of abnormalities without human intervention. This can lead to cost savings, increased energy production, and improved overall performance of solar PV systems. Furthermore, the use of unsupervised sensing algorithms and 3D augmented reality visualization techniques adds a new dimension to the field of solar PV maintenance, opening up possibilities for further research and development in this area.

However, the incorporation of human judgment is pivotal to ensure the accuracy and reliability of anomaly detection in PV, especially considering the complexity and variability of anomalies in PV modules including hot spots, micro-cracks, potential-induced degradation (PID), snail trails, light-induced degradation (LID), delamination, etc. This necessity for expert analysis, hence, does increase the costliness of our method.

Future work will focus on mitigating the necessity of expert human analysis in detecting anomalies in PV modules. Typically, several strategies could be implemented. Enhancing the precision of unsupervised sensing algorithms through machine learning, employing deep learning models like CNNs for defect recognition, and establishing semi-automated systems for initial AI screening with human experts reviewing critical cases can significantly improve efficiency. Augmenting data with simulated defects, leveraging a crowdsourced approach for data analysis, and instituting a continuous learning loop with real-world feedback can evolve the system's accuracy. Additionally, integrating anomaly detection with predictive maintenance, refining augmented reality tools for better visualization, collaborating with regulators for industry standards, and developing a feedback mechanism from technicians' repairs will collectively diminish the reliance on human judgment, thereby reducing costs and enhancing the method's scalability.

Solar Photovoltaic (PV), Augmented Reality (AR), True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN) and Intersection over Union (IoU) are abbreviations whereas.

CRediT authorship contribution statement

Adel Oulefki: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Yassine Himeur:** Writing – review & editing, Writing – original draft, Project administration, Funding acquisition. **Thaweesak Trongtirakul:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Kahina Amara:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Sos Agaian:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Samir Benbelkacem:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Mohamed Amine Guerroudji:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Mohamed Zemmouri:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Sahla Ferhat:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Nadia Zenati:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Shadi Atalla:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Wathiq Mansoor:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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