Cureus Journal of Engineering

Open Access Review Article

Performance Evaluation and Degradation Assessment of Photovoltaic (PV) Modules

Received 05/25/2025
Review began 06/16/2025
Review ended 08/23/2025
Published 09/10/2025

DOI:
https://doi.org/10.7759/s44388-025-06969-5

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Abstract

In the current landscape of escalating energy demands, photovoltaic (PV) systems have emerged as a pivotal solution for sustainable electricity generation. However, the efficiency and longevity of these systems are often compromised by various faults, such as hotspots, which can lead to significant energy losses and potential safety hazards. Traditional inspection methods for PV modules are often labor-intensive, time-consuming, and may not effectively detect subtle anomalies. To address these challenges, the integration of thermal infrared (IR) imaging with advanced deep learning algorithms offers a promising avenue for enhancing fault detection capabilities. Thermal IR imaging enables the visualization of temperature variations across PV modules, facilitating the identification of defects like hotspots that are indicative of underlying issues. When combined with deep learning techniques, particularly convolutional neural networks, the system can automatically analyze thermal images to detect and classify faults with high accuracy. Implementing such an approach not only improves the precision of fault detection but also allows for real-time monitoring of large-scale PV installations. Early identification of minor faults can prevent their escalation into major failures, thereby reducing maintenance costs and minimizing downtime. This study proposes the development of a deep learning-based framework utilizing thermal IR imaging data to detect and classify faults in PV modules. By leveraging this integrated approach, the goal is to enhance the operational efficiency and reliability of PV systems, contributing to the broader adoption of renewable energy solutions.

Categories: Renewable Energy Systems, Sustainable Technologies, Environmental and Sustainable Engineering
Keywords: sustainable, photovoltaic (pv) modules, fault detection, imaging techniques, deep learning, faster rcnn

Introduction And Background

Considering the future demands and requirements for energy, the focus is shifted toward the usage of renewable energy for electricity production. Major government initiatives are in line with the goals of the United Nations (UN) toward sustainability. For 20 years, the setting up and production of photovoltaic (PV) plants to meet the ever-increasing demand for electricity has increased widely. The environmental impact of solar panels is increasing day by day, even after their economic life is achieved. Disposal of such used panels is creating problems; meanwhile, even in its operating hours, the efficiency is found to be variable at different places [1-3]. Solar energy proves to be cost-effective if the devices are efficiently used for a longer duration of time, which differs based on geographical conditions [4,5].

Due to severe climatic and local conditions, the PV panels are getting damaged, resulting in the formation of various types of faults. Notable damages have affected the performance and energy efficiency of the PV modules, resulting in major losses. Monitoring the PV modules for fault detection over a larger area is the thrust area of today's research. Inspection methods are needed to detect PV module failures. Special reference to failure in the form of faults is significantly affecting the power generation efficiency of PV plants. Excess photon energy and less photon energy relative to a bandgap are the factors influencing the efficiency reduction by more than 50%. Other than photon energy, voltage factor, curve factor, top surface contact obstruction, reflection at the top surface, and series and shunt resistance are minor factors affecting the efficiency of PV modules [6]. Many researchers have tried experimental-based, image-driven data for finding faults or diagnosing defects at various locations separately. Visual inspection methods, current-voltage characteristic methods, thermal/infrared (IR) imaging methods, and electroluminescence imaging methods are a few of the methods/techniques that are gaining importance due to their versatile nature. The study focuses on the comparative analysis of these methods, attempting to bridge the gap by comparing various methods and suggesting the most suitable through a systematic scoping method. Confronts and opportunities are well documented in the present work related to the techniques discussed in detail. Furthermore, the discussion is enhanced on the thermal/IR imaging method for its probable further use in a case study [2-6].

PV module failures and detection techniques

Kinds of PV Array Faults

Failure of PV modules due to debris, cracks, hotspots, and soiling, as reported in Figure *1*, is the major types of failure of PV modules, which are further briefly classified into physical, electrical, and environmental faults, as reported PV module faults as shown in Figure *2*.

Causes of Hotspots

Hotspot faults in PV modules arise from issues like shading, soiling, dust accumulation, series resistance, and cell damage. These hotspots, which are not visible to the naked eye, result in localized high temperatures that negatively impact power output by reducing current flow and causing voltage issues. If untreated, they can lead to failures in PV modules due to problems such as local shunts, p-n junction deformation, and impurities.

PV modules are crucial for generating electricity, but various faults can lead to power loss or system failure. Factors affecting their efficiency include sunlight intensity, shading, dust accumulation, and mechanical stresses. Faults can be categorized into physical, electrical, and environmental types and common causes. Degradation faults, which are caused by water ingress or temperature stress; glass break faults, resulting from improper handling or mechanical loads; cell break/micro-cracks arising from mechanical stress and environmental factors like weather and aging; glass delamination, linked to poor construction, low-quality materials, and moisture; corrosion faults, which occurs when moisture or gases penetrate through cracks; snail trail faults, discoloration lines from long-term use, often near bus bars or cracks; hotspot faults, which result from partial shading, mismatched cells, and high temperatures; open circuits, which happens when internal cables disconnect or due to faulty diodes; bypass diode faults, which prevent hotspots by redirecting current during shading or faults, affected by lightning or thermal issues; short circuits, caused by poor connections or manufacturing defects; ground faults, which occur due to insulation failure, leading to unintended current paths; arc faults, resulting from installation errors or component failures. Understanding these faults is essential for maintaining PV module efficiency and reliability.

Fault Detection Techniques

Table *1* demonstrates various fault detection techniques, which are classified into data analytic methods, visual and imaging methods, and electrical devices/methods. From Table *1*, among various fault detection techniques, thermal/IR imaging is the most effective for identifying and localizing faults. This method facilitates data collection, which can be analyzed using deep learning algorithms to detect and locate hotspots. Specifically, the FRCNN (Faster Region-based Convolutional Neural Network) method, which is based on region proposals, is employed in this advanced approach.

Data Analytic Methods (Detect and Identify (DC & AC Faults))	Visual and Imaging Methods (Detect and Localize PV Array Faults)	Electrical Devices/Methods (Detect and Localize Specific Faults)
Climatic data independent technique (RLC)	Visual Inspection	Detection and interruption due to ground faults
Electrical current-voltage measurement technique (at output terminal)	Visual Camera	Analysis of the voltage and current using frequency spectrum waveforms
Contrast between measured and modeled PV system output techniques	Thermal/Infrared (IR) imaging	Insulation monitoring devices
Power loss analysis technique (losses in PV module)	Electroluminescence (EL) imaging	Arc fault circuits Interrupt
Artificial Intelligence (AI) techniques (depends on learning, training)	Unmanned Aerial Vehicle (UAV)	

TABLE 1: Fault detection techniques

FIGURE 1: Examples of PV module failure due to hotspot on PV module

PV, photovoltaic

Review

Technique	Principle	Advantages	Limitations	Best Use Case
Visual Inspection	Direct human or camera-based observation of module surfaces	Simple, low-cost, quick; scalable with drones; detects surface defects (cracks, delamination, corrosion)	Limited to surface-level issues; cannot quantify performance loss	Initial large-scale screening
Infrared Thermography	Detects infrared radiation to map temperature distribution	Fast, drone-enabled for utility-scale; identifies hotspots, bypass diode failures, interconnect issues	Requires sunlight/irradiance; may miss latent or non-thermal defects	Field-level rapid hotspot detection
Electroluminescence (EL) Imaging	Module forward biased → defects emit luminescence; captured by IR-sensitive camera	High-resolution; detects microcracks, PID, solder failures, interconnect defects	Requires dark conditions or shading; slower, less scalable	Detailed module diagnostics
Ultraviolet Fluorescence (UVF) Imaging	UV excitation causes encapsulant to fluoresce; reveals degradation patterns	Sensitive to encapsulant browning, delamination, potential corrosion	Mainly qualitative; weak signal in some materials; less field-friendly	Research and laboratory degradation studies
Light Beam Induced Current (LBIC)/EBIC	Scans with focused light/electron beam → maps current response	High spatial resolution; useful for pinpointing microdefects in cells	Requires lab setup; destructive for full module inspection; slow	Cell-level defect characterization
Photoluminescence (PL) Imaging	Excites carriers with light → records emitted photons	Non-contact, high sensitivity to cracks and defects, usable in light conditions	Lower resolution vs. EL; sensitive to background light	Rapid cell characterization, manufacturing QA
UV-Vis-NIR Reflectance/Transmittance Imaging	Measures optical absorption/reflection	Identifies soiling, coating defects, optical degradation	Limited electrical info; not widely standardized	Optical performance studies

TABLE 2: A comparative table summarizing various imaging methods

PID, Potential Induced Degradation

Literature review

Hong et al. reviewed PV fault detection and classification as crucial for keeping the reliability of PV systems [7] (Table 2). Khaled et al. in this paper examine operational faults in PV systems that impact performance and energy production [8]. The analysis focuses on causes, effects on performance, and practical applications, providing a foundation for enhancing PV system reliability and suggesting future research directions. Li et al. reported that the fast expansion of PV skills requires effective health monitoring plans for reliable operation and energy availability [9].

Visual Inspection Method

Jalal et al. examine the vulnerabilities of PV systems to environmental factors and underscore the necessity of visual inspections for identifying faults, rather than relying solely on onsite detection methods [10].

Sripada et al. present a novel stacking-based ensemble approach for classifying visible faults in PV modules using aerial images [11]. Naveen et al. introduce an ensemble-based deep neural network (DNN) model for autonomously detecting visual faults in PV modules. The approach integrates well with commercial Unmanned Aerial Vehicle (UAV) flight management systems for efficient fault detection [12]. Sridharan et al. present a new voting-based ensemble technique for diagnosing visible faults in PV modules using drone-captured aerial images. It addresses issues like glass breakage, snail trails, burn marks, delamination, and discoloration. This technique enhances fault diagnosis accuracy while reducing inspection costs and efforts, promoting sustainable PV system operation [13].

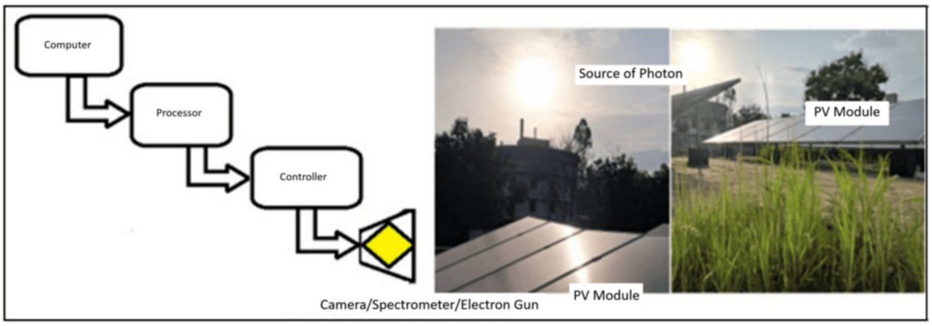

FIGURE 2: A simplified schematic diagram of imaging for PV module for fault/defect identification through various methods

PV, photovoltaic

Current-Voltage Characteristic Method

Gabriel et al. reported an in situ monitoring and alerting system using Wireless Sensor Network technologies for early detection of Potential Induced Degradation (PID) and hotspots in solar parks. It emphasizes the need for periodic monitoring of key parameters like temperature, humidity, irradiance, current, and voltage at the panel level. Data collected are processed on a cloud-based platform, where diagnostic algorithms analyze the information. While previous methods, like Gabrielet's, focused on electrical parameters to detect hotspots, the study proposes that deep learning techniques could improve accuracy and efficiency in identifying these issues, optimizing the monitoring process [14].

Taghezouit et al., in the paper, review the growing significance of solar PV systems as renewable energy sources, addressing the risks posed by faults and anomalies that can hinder their performance [15].

Dhoke et al. propose generating fault pointer signals or residuals for each module string and comparing these against a threshold to detect faults [16].

Thermal/Infrared Imaging Method

A cluster of circuits and solar panels can be effectively checked using the safest and contactless thermography technique. IR imaging or the thermography technique was initiated in the last decade of the 20th century [17,18]. For obtaining an IR thermographic photo, an IR camera should be used. The thermal sensitivity of the camera, sufficient solar irradiance, and the imaging angle should be properly maintained to get more accurate IR thermography [19].

Module errors are detected in the following manner through thermal imaging:

· A hot or cold spot, a cell heating type of thermal image, indicates impurities, gas pockets, cracks in the cell, and a portion of the section appears hotter as a result of cracks in cells. This all comes under the manufacturing and/or processing-induced defects or damage.

· Hot spots are related to pollution, bird droppings, and humidity, which are due to temporary shading.

· A module or string of modules that appear consistently hotter is an example of modules that are not connected, which is a defective bypass diode fault or bad interconnection.

Pathak et al., in the paper discusses the significant growth of PV energy in the last decade, emphasizing the increasing complexity of solar power plants and the need for advanced condition monitoring systems. It introduces a novel method for detecting faults in PV panels using thermal images from a thermographic camera [20]. Pathak et al., in this study, explore the use of thermal imaging for detecting faults in solar panels, The research identifies five fault types: single cell, multicell, diode, dust/shadow, and PID hotspots, and evaluates the impact of pre-processing techniques like filters and histogram equalization on fault detection accuracy [21]. Muhammad Umair et al. reviewed a study focused on classifying thermal images of PV panels into three categories: healthy, non-faulty hotspots, and faulty. It utilized a hybrid machine learning algorithm based on support vector machines (SVMs), which showed efficient storage requirements. The algorithm achieved a training accuracy of about 96.8% and a testing accuracy of 92%. Furthermore, the study highlights the increasing demand for solutions that move beyond hotspot classification [22].

Ahmed et al. utilized IR thermography to report that PV systems are valued for their renewable energy capabilities but face operational and environmental challenges that require effective monitoring. The method achieved a notable 97% accuracy in testing, demonstrating efficiency and low computational requirements [23]. Ali et al. present a study that introduces a hybrid feature-based support vector machine model that employs IR thermography to detect and classify hotspots in PV panels. The method demonstrates a training accuracy of 96.8% and a testing accuracy of 92% [24]. Kim et al. introduced an algorithm that segments images into individual solar cells, enabling precise assessment of temperature variations that signal defects. The results show that enhanced images provide clearer features for analysis [25].

Chen et al. introduced two approaches for detecting hotspots in IR images of PV modules. It is learned that the deep learning method shows enhanced performance but demands greater computational resources [26]. Dhimish et al. address the issue of PV hot spots, where certain cells in PV modules overheat, resulting in power loss and decreased performance. The study found that DC classifiers offered the maximum detection correctness at 98%, while decision trees had the lowest at 84% [27]. Lofstad-Lie et al. introduce a two-stage autonomous flight strategy to enhance efficiency and reduce costs. Simulations and real data show that this method can save up to 60% of operational time, particularly in plants with defect densities of 0.5% to 1%, and is particularly effective for high-latitude geometries [28].

Su et al. reviewed the article addressing the challenge of detecting overheated regions in PV modules during routine inspections. Experimental results show that this approach significantly surpasses traditional methods in effectiveness and efficiency [29]. Wei et al. and Shuoquan et al. introduce two methods for detecting hotspots in IR images of PV modules: one uses traditional digital image processing techniques, such as Hough line transformation and the Canny operator, while the other leverages a deep learning model based on Faster-RCNN and transfer learning, which enhances performance but demands greater computational resources [30,31]. Yang et al. observed that this work introduces a method for detecting cracks in steel sheets using IR thermal imaging combined with Convolutional Neural Networks (CNNs), addressing the limitations of traditional vision-based methods [32].

Zefri et al. reviewed the increasing adoption of PV technology, highlighting the need for efficient inspection methods. This study introduces a deep learning model designed to detect defects in PV modules using thermal IR imagery [33]. Haidari et al. introduce a new approach using deep learning for inspecting PV systems. By using thermal images from both aerial and terrestrial sources to build a dataset, the deep learning model achieved a high accuracy of 0.98 [34]. Behzadi et al. explore the impact of concentration factor on crystalline silicon (c-Si) and copper indium gallium selenide (CIGS) PV technology, specifically assessing CIGS's suitability for low-concentration PV applications [35]. Aman et al. reported that solar panel performance is influenced by temperature, sunlight exposure, dust accumulation, and shading. This analysis aids in more effective and cost-efficient inspections of PV modules for defects [36]. Tianyi et al. (2022) categorization of the hot spots of PV modules is circular, linear, and array. The study presents a novel method that utilizes anchors of varying sizes and employs the YOLOv5 (AP-YOLOv5) network for detecting hotspots in PV panels. From the study, it is observed that a more rigorous method, such as Faster R-CNN, can achieve greater accuracy than YOLOv5 methods in detecting hot spots [37].

Fuchang et al. presented that the improved Rotation Forest (RoF) algorithm, when hybridized with Extreme Learning Machine (ELM), has shown enhanced accuracy in fault diagnosis of PV arrays compared to basic RoF and ELM methods. The advanced RoF effectively detects hot spots in PV systems. However, for even greater accuracy and speed, incorporating more rigorous techniques like FRCNN is recommended [38]. Han et al. outline a two-step process of feature selection and classification. The algorithm divides the feature space into subspaces, determines optimal subsets through a search process, and employs bootstrap resampling and principal component analysis (PCA) for sample transformation [39]. Aqdas et al. utilize a machine learning-based algorithm, a non-linear Gaussian posterior distribution via Gaussian Process Regression (GPR), to detect, classify, and localize faults in PV systems. Despite requiring a longer training time, the rational quadratic GPR demonstrated the lowest root mean squared error during validation, indicating its effectiveness in accurately modeling and predicting fault characteristics in PV systems [40]. Cardoso et al. present new monitoring technologies designed to increase the performance and reliability of PV installations. This automated approach supports detailed solar panel monitoring and aids in real-time PV monitoring, solar resource simulation, and digital twin development [41].

Casini et al. examine the rising use of deep learning methods for calculation in the energy sector through a systematic literature review. A schematic correlation chart is included to illustrate the relationships between algorithms, tasks, and applications, aiming to shed light on current trends and future developments in energy-related deep learning applications [42]. Amit et al. present a simple method to improve the Average Precision (AP) of object detectors using Stochastic Weight Averaging. The aim is to raise awareness of this technique and provide their code for further experimentation by researchers [43].

Chen et al. emphasize that dense instance segmentation uniquely outputs geometric structures for each spatial location. Results demonstrate significant improvements over traditional methods, achieving performance comparable to Mask R-CNN. The findings suggest that Tensor Mask could be pivotal for future developments in dense mask prediction, with code set to be released for further research [44]. Fan et al. introduced an open-source deep-learning library focusing on video understanding tasks, including classification, detection, and self-supervised learning [45]. Cheng et al., in the paper, present boundary intersection over union (IoU), a new segmentation evaluation metric that focuses on boundary quality. It shows that Boundary IoU is more sensitive to boundary errors in large objects than the traditional Mask IoU, while still being fair to smaller objects [46].

Javaid et al. present a machine learning-based Gaussian process regression algorithm for detection, categorizing, and localizing faults in PV systems by assessing solar cell parameters to determine fault severity [47]. Michail et al. review diagnostic methods for PV plants, focusing on UAVs that use imaging and data-driven analytics. The study summarizes the operating conditions and types of failures detectable by these methods [48]. Moradi Sizkouhi et al., in this study, present an autonomous method for detecting defects in PV modules, focusing on the impact of bird droppings [49]. Oulefki et al. review solar PV systems as essential for global energy security, but their efficiency can be affected by issues like hotspots and module cracks. A new methodology has been developed to automatically detect and analyze these problems using unsupervised sensing algorithms combined with 3D Augmented Reality for better visualization [50].

Prabhakaran et al. reported that the real-time multi-variant deep learning model for defect detection and classification uses a pre-processed image dataset enhanced by the region-based histogram approximation algorithm. By integrating deep learning with advanced image processing, this model enhances the accuracy and efficiency of defect detection [51]. Prashanth et al. present a novel approach that combines deep neural networks and machine learning to diagnose faults in PV modules. Experimental results demonstrate a remarkable accuracy of 98.57%, marking a significant advancement in enhancing the reliability and performance of PV systems [52].

Segovia et al. present a new approach using two consecutive CNNs within an IoT framework to enhance hot spot detection while significantly reducing false positives [53]. Sepúlveda-Oviedo et al. reported conventional fault detection methods in PV systems to struggle with the large, high-dimensional data produced by modern monitoring technologies [54]. Vlaminck et al. present a novel drone-based system for diagnosing issues in PV plants, addressing the need for regular inspections as solar energy usage increases [55]. Aziz et al. observed that fault diagnosis in PV arrays is crucial for maximizing efficiency and reducing maintenance costs [56]. Bakır et al. study focuses on enhancing the performance and reliability of PV installations through advanced monitoring technologies [57]. Bouazzi et al. discuss the challenges of dynamic climatic conditions and uncertainties affecting renewable energy conversion systems, which can lead to performance and maintenance issues [58]. Fernandes et al. highlight common failures in key components of conventional PV solar plants and recommend strategies to mitigate unexpected failures, illustrated with photos from solar PV plants in Portugal [59].

Electroluminescence Imaging Method

Karimi et al. utilized image characterization techniques to detect signs of degradation, such as busbar corrosion cracking and dark spots, through periodic EL images from accelerated exposure tests. The research promotes a scalable and unbiased approach for monitoring PV module health, offering insights into degradation mechanisms. Advanced feature extraction and PCA enhance the identification of degradation patterns, using Google's TensorFlow for computational efficiency [60]. Sohail et al. propose a deep learning approach to detect various types of cracks in PV cells, focusing on crack orientation. Four deep learning models such as U-net, Link Net, FPN, and attention U-net are trained and compared using an online dataset of electroluminescence images. Performance is assessed through metrics like IoU and F1-Score, with an ensemble learning technique improving segmentation accuracy, thereby enhancing PV system health monitoring and efficiency [61].

Methodology

The present work is a rigorous study of available literature for which the systematic scoping review technique as mentioned by Moher et al. [62], is implemented for selecting and interpreting the articles obtained from the standard journals, books chapters, reference books, and conference papers based on the identification and localization of faults and/or degradation examination techniques. To initiate the overwhelming task of determining the appropriate, relevant, and recent databases of our interests, many keywords like PV module fault detection, PV module fault detection methods, PV module degradation detection techniques, and PV module defect diagnosis methods/techniques/approaches were used. Overall, the searching operation has PV module as a common terminology. For the literature selection process, standard platforms like Elsevier, Springer, IEEE, etc., are considered of top priority. The review process was carried out on the filtered literature, which had to undergo scrutiny of recent, relevant, and closely associated studies. Maadadi et al. explore various materials, emphasizing their potential for optoelectronic and PV applications [63]. Arabi et al., in the material synthesis strategy presented in this study, state it is facile, rapid, and simple [64]. The reported work was thoroughly reviewed, and the findings and gaps were extracted as input for the present work.

Furthermore, the work will be extended to carry out the defined methodology on a realistic problem. First of all, the pre-processing of the thermal image will be done, followed by the generation of a convolution feature map of the region proposal network. This feature map is passed through the region of interest pooling layer, which generates the fixed-size anchors and feature map. Once the feature map is obtained, the next step is to flatten it and send it to a fully connected layer. It will be passed through the regression layer, which localizes the bounding box on the hotspot.

FRCNN is a popular deep-learning model for hotspot fault detection. It significantly improves the speed and accuracy of hotspot detection tasks by combining CNNs for feature extraction and generating object proposals. The processes are as follows:

· Input Image: The input to FRCNN is a single image of size H × W × C, where H is the height, W is the width, and C is the number of channels.

· Pre-processing of Images: Pre-processing of Images is carried out in this block.

· Feature Extraction: This step involves feeding the image to extract feature maps from the image to generate a set of feature maps that contain important information about the hotspot fault content in the image. After the region of interest pooling, the feature vector is passed through fully connected layers. Bounding box regression: this layer refines the coordinates of the bounding boxes further to improve their localization.

· Final hotspot fault detection, the final output of FRCNN is a set of detected hotspot faults.

The application of AI, specifically FRCNN deep learning technology, as identified through a literature survey, is found to be the best alternative for evaluating the performance and degradation of PV modules.

In PV module fault detection using thermal imaging, the main challenge is accurately localizing hotspots (caused by cracks, soiling, shading, or internal defects). Conventional image-based fault detection techniques (thresholding, morphological operations, clustering, etc.) rely mostly on pixel intensity distributions in the IR spectrum. The integration of FRCNN enhances hotspot localization in PV modules by leveraging region proposals, deep learned features, and bounding box refinement, which results in more robust, accurate, and scalable detection compared to conventional intensity- or segmentation-based techniques that are sensitive to noise, scale, and environmental variations. Traditional methods typically depend on features like intensity, and shape. FRCNN automatically runs relevant features from training data using convolution layers, and it generates smart proposals for hotspot locations, filtering out irrelevant reasons.

Conclusions

Observations and conclusions

The following observations are highlighted from the reported work.

It is observed that several researchers have already reported the usefulness of traditional methods and electrical parameters to find hotspots, and some have classified hotspots. But instead of classification, a direct solution-finding approach should be applied.

The exact location of the fault in the form of a hotspot can be identified using the Thermal/IR imaging method, unlike other methods like visual inspection, etc.

There is a need for monitoring PV modules with advanced deep learning-based algorithm techniques to detect faults. Further, based on the outputs, it is intended to expand on this aim to achieve total anatomy by making use of automated drones.

Time-saving and cost-management parameters should be considered for monitoring PV modules to detect faults.

Advanced techniques for calculating PV module efficiency are proposed to be used in further study.

Dataset creation and augmentation involve compiling a comprehensive dataset of thermal images containing both normal and hotspot-affected PV panels. This dataset needs to encompass various weather conditions, shading scenarios, and types of hotspots.

Development of a robust deep learning model design and train a model tailored for the identification and localization of hotspots on PV module is a thrust area.

Evaluate and validate algorithm performance by utilizing metrics such as mean AP, precision, recall, and score to quantify the model's performance. Implement the developed algorithm into real-world PV systems for practical testing and validation.

A more accurate RCNN can be applied for improved accuracy and speed. Deep learning serves the purpose of finding hotspot faults easily instead of using the tedious method of using electrical parameters.

It is learnt that the flaws which are observed in the traditional methods are appropriately addressed if a developed framework based on deep learning using thermal IR imaging is adopted for fault detection and classification in PV modules. On one side, the traditional methods are time-consuming and tedious, while deep learning processes a large volume of thermal images, giving a real-time solution. Threshold or manual interpretation is highly required in traditional methods, whereas the deep learning models (CNNs, FRCNN, YOLO, etc.) learn complex spatial and thermal patterns, allowing precise detection and classification of faults such as hotspots, soldering issues, bypass diode failures, and cracks. Deep learning-based thermal analysis provides a pixel-level localization, highlighting defective regions directly in the module image. From the mentioned highlighted points, it is clear that the combination of deep learning techniques, particularly CNNs, enables the system to automatically analyze thermal images to detect and classify faults with high accuracy, which will not only improve the precision of fault detection but also allow for real-time monitoring of large-scale PV installations.

The usefulness of imaging techniques for the detection of faults is highlighted in PV modules, starting from the visual inspection method, current-voltage characteristic method, thermal/IR imaging method, ultraviolet fluorescence imaging method, electroluminescence imaging method, scanning electron microscopy imaging method, electron beam induced current imaging method, clustering-based computation method, etc. This paper has shown that the easiest way to identify the faults or the degradation in a contact-less and safe manner is to use any of the mentioned imaging techniques.

A field investigation followed by an analytical study using a tailor-made methodology would serve the purpose once validated with reported case histories. It is learnt that monitoring of thermal images taken from the field to detect and localize hotspot faults using a deep learning-based algorithm, FRCNN, is the thrust area which may prove to be a better option to solve the real-world problems, proving to be a sustainable alternative.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Anand B. Tapase, Rajashree B. Tapase, Shamala Mahadik

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Supervision: Shamala Mahadik

Disclosures

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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