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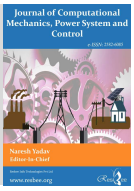


Image Processing Techniques for Photovoltaic Panel Hotspot Fault Prediction: A Comprehensive Survey

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Abstract: In order to lessen reliance on fossil fuels and mitigate environmental effects, solar photovoltaic technology is used. Even so, a number of flaws can seriously compromise the efficiency and long-lasting nature of solar systems. The area of Photovoltaic (PV) modules with the greatest thermal accumulation is called a hotspot. Hotspots are often caused by cell mismatch, partial shading, manufacturing defects, or aging-related degradation of PV modules. However, the long-term exposure of PV panels can decrease the efficiency of power generation and even start fires due to the hostile conditions of mountains and deserts. Thus, the conventional electrical and image processing methods have become effective in recent years. There are several types of classifiers employed in image processing methods to forecast the PV panel's hotspot problem. Similarly, the modern image processing and computer vision methods for hotspot defect prediction in PV panels are reviewed in this extensive survey. These methods include thermal infrared imaging, electroluminescence, visible-light imaging, and drone-based inspection systems. The paper examines DL frameworks, ML techniques, and traditional algorithms for hotspot detection, segmentation, classification, and prediction diagnosis. The survey conducted a literature review that focused on the most significant papers published in IEEE, Springer journals, Science Direct, and Google Scholar between 2020 and 2025 in order to provide a thorough summary of the present research. These studies were analysedby utilising techniques that account for specificity, accuracy, efficiency, and convergence time. Comparative performance analysis is carried out to identify the most reliable and computationally efficient approaches. This survey also presented obstacles and limitations of the model in order to encourage future advancements in image processing techniques for solar panel hotspot fault prediction.

Keywords: Photovoltaic panels; Thermal Infrared Imaging; Hotspot Fault Prediction Approach; Processing Technique; Learning Approach

Nomenclature

Abbreviation	Description
PV	Photovoltaic
IR	Infra-Red
ICNM	Isolated Convolution Neural Model
RCNN	Region-based CNN
SK-FRCNN	Selective Kernel-Faster RCNN
EL	Electro-Luminescence
ML	Machine Learning
DL	Deep Learning
UAV	Unmanned Aerial Vehicle
CNN	Convolutional-Neural-Network
k-NN	k-Nearest Neighbor
MSER	Maximally Stable Extremal Regions
rgSIFT	Red-Green Scale-Invariant Feature Transform
LGBPHS	Local Gabor Binary Pattern Histogram Sequence
YOLOv5	You Only Look Once
ResNet	Residual Network
GBH-YOLOv5	Ghost convolution with BottleneckCSP and a tiny target prediction head incorporating YOLOv5
PAN	Path Aggregation Network
ResNet 50	Residual Network 50
MobileNetV2	Mobile Network Version 2
ResNet 18	Residual Network 18
mAP	Mean Average Precision
FPN	Feature Pyramid Network
IoU	Intersection over Union
2TSS	Two-tier Semantic Segmentation
ViT	Vision Transformers
NAS	Neural Architecture Search
ROI	Region of Interest

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1. Introduction

Generally, PV panels are a device that converts solar radiation into electricity. They are made of semiconductor materials[1]. In recent years, the rapid expansion of large-scale solar farms has further increased the demand for reliable monitoring and diagnosis of PV systems. In this panel, due to the series connection of the circuit and continuous power consumption, the short-circuit current is lowered. This effect raises the temperature and speeds up the PV cell's degradation [2]. With the applications of autonomous navigation, industrial inspection, medical imaging, remote sensing, and renewable energy systems, the image processing method was used, and it became a flexible and effective method for the detection [3][4]. These crucial applications are used in thedetection and forecasting of hotspot flaws in PV panels, where image analysis methods are essential to preserving the dependability and efficiency of solar power production [5][6]. However, the hotspot faults are caused by abnormalities like shade, fractures, or dust accumulation that result in unequal current distribution and localized heating [7]. These irregularities often develop silently over time, making automated detection systems particularly valuable. Thus, for the purpose of preventing irreversible damage, guaranteeing safety and improving overall energy is necessary for this process; similarly, the early and accurate diagnosis of such problems is essential [8]. Mostly, the long-term exposure can cause photovoltaic panels to crack and sustain damage because of the UV radiation, heat cycling, and thunderstorms [9, 10]. These problems will cause solar panels to heat up, which will result in hot-spot failure. Similarly, heat is released, and power generation efficiency is decreased as a result of hot spots consuming power produced everywhere in the panel. As the temperature rises, the panels' jointlinkages may melt, causing damage and a fire [11][12]. Therefore, early monitoring technologies capable of operating under varying environmental conditions become critical for safety assurance. The existing work offers a comprehensive analysis of image-processing-based techniques for hotspot fault prediction in PV systems. In order to analyze thermal and electroluminescence images of PV modules, the study focuses on the entire analysis channel from image acquisition for segmentation and classification improvement [13][14]. Moreover, particular attention is given to feature extraction methods that extract important thermal, spatial, and structural information from images, as well as intelligent classifiers that use these characteristics to accurately differentiate between faulty and healthy regions [15].

The various surveys are employed about the classical image analysis, which has been turned into automated fault prediction systems to handle vast and diverse datasets because of developments in computational intelligence [16][17]. These automated systems significantly reduce manual inspection efforts and enable continuous monitoring at scale. Similarly, the accuracy, robustness, and scalability of current methods are compared, emphasizing the increasing direction toward hybrid and intelligent frameworks [18]. In this PV hotspot prediction model, there are several issues, including dataset standardization, illumination change, and real-time implementation, which are addressed, along with possible research roads for developing hotspot prediction models that are more flexible and accessible [19, 20]. The goal of this paper is to give image processing surveys for the extensive understanding of the approaches, potential, and difficulties associated with using computer vision for the investigation and prediction of PV panel hotspot faults. The contribution of the survey is to classify and assess ML models, contemporary DL architectures, and traditional image processing techniques for hotspot detection, segmentation, and classification. Additionally, this article compares the specificity, computational complexity, and accuracy of the literature. However, the classical image processing, shallow ML, DL, semi-supervised learning, meta-heuristic, and optimization-enhanced models are among the image processing methods for solar panel hotspot fault prediction that are methodically examined. Additionally, the survey provides insights into emerging trends such as self-supervised learning and multimodal fusion for improving prediction performance. Furthermore, it draws attention to the existing shortcomings in the accessible PV fault datasets and performance benchmarks, highlighting the necessity of standardized methodologies to impartially assess hotspot detection systems.

This paper is structured as follows: Section 1 offers a summary of solar power prediction. State-of-the-art research is reviewed in Section 2. In a comparable manner, Section 3 gives a detailed analysis of several methods employed in the current work. The study and explanation of the many techniques employed in the current prediction process are presented in Section 4. Section 5 outlines research shortcomings, while Section 6 emphasizes the work's conclusion and future scope.

2. Research based on the State of the art

To improve the detection efficiency of a PV fault detection model, several techniques have been proposed. In recent years, these techniques have evolved rapidly due to advancements in computing power and sensor technology, enabling more sophisticated analysis of thermal and visual data. The PV fault/hotspot

detection algorithm incorporates extensive use of DL and infrared thermography in these surveys. Similarly, by proving that thermal imaging combined with ML/DL can identify and locate PV hotspots with high reported accuracy, the surveyed works together advance the state of the art. According to this survey, the accuracy and mAP/F1 scores for the provided articles are high (many >95%), but direct comparisons are challenging because of the large variations in datasets, evaluation techniques, and issue formulation (classification vs. detection vs. segmentation). However, in order to address the gap between encouraging lab results and widespread industrial adoption, the field would greatly benefit from standardized, public datasets; rigorous cross-site evaluations; domain-adaptation techniques; uncertainty-aware architectures; and explainability.

In order to find hotspots and errors, DL and infrared thermography have been extensively utilized in recent PV fault detection research. With growing PV installations worldwide, the demand for scalable and automated fault detection methods has increased significantly. Similar to this, early techniques used image processing and manually created features such as rgSIFT with k-NN [1], which demonstrated strong performance on small datasets and achieved up to 98.7% accuracy. Conventional vision methods like thresholding and MSER [10] also demonstrated efficacy with approximately 97% accuracy. However, the CNN-based classification, which achieves 97–100% accuracy on controlled datasets, is becoming more and more popular in contemporary research [3][12]. Similarly, lightweight models, such as ShuffleNetv2 [4] and MobileNetV2 [9], allow for high precision and quick real-time deployment, up to 49 frames per second. These lightweight architectures are especially suitable for edge devices installed on drones or field robots. Similarly, with mAP gains exceeding 27%, YOLO variants significantly improve the detection of small errors. New research focuses on attention mechanisms and semantic [16][20], enhancing pixel-level localization and obtaining >98% F1-score. In large-scale field inspections, UAV-based systems perform well, obtaining >99% accuracy.

Thus, the state-of-the-art is driven by several methods, which provide high automation and accuracy. The continuous integration of AI, advanced imaging, and autonomous platforms is reshaping the future of PV maintenance. Nevertheless, the majority of research relies on small private datasets and has poor generalization tests across many positions and climatic circumstances. For industrial-scale PV inspection, there is still a need for domain-adaptive systems, lightweight explainable models, real-world benchmarks, and public datasets.

3. Survey of Different Methods Used in the PV Panel Hotspot Fault Analysis and Prediction Model

(i) Based on Processing Technique

(a) Classical Image Processing

In 2022, Kirubakaran et al. [2] suggested a method for processing thermal images and identifying the panel using a thermal imaging device. The image processing model could process both the fault prediction and thermal images. Furthermore, the method demonstrated that basic thresholding and temperature-gradient observation remain effective for quick fault screening. This proved that thermal imaging captures hotspots. Similarly, the image processing technique was used to compare the new and old solar photovoltaic panels since any defects in the panel were identified as hot spots. In a similar vein, the aged panels' image revealed hot areas, and performance was assessed according to recognized standards. The outcomes of the experiment were confirmed.

In 2020, Jeong et al. [10] developed a method for analyzing images that automatically determining which solar module was producing the hot spots. They extracted feature points using the MSER technique, which leverages the PV module's blue type to identify the area of interest using the in-range function. They proposed an effective feature point matching technique as well as a homography translation strategy. These geometric transformations helped minimize alignment errors during panel mapping. To improve performance, the normal/abnormal decision process and the temperature data derivation method were explained. Experiments were used to assess the suggested system's efficacy. A thermal imaging examination of over 240 modules was found to be 97% consistent with a visual examination of the trial outcomes.

(b)Shallow ML Techniques

In 2022, Ali et al. [1] proposed a novel framework that uses an ML algorithm and colour image descriptors for early hotspot detection in PV panels. Using the suggested procedure, the resulting thermographic images of PV panels were divided into non-overlapping sections, and colour image descriptors were subsequently calculated for each area. After thorough testing and analysis, the experimental results demonstrate that, with an accuracy rate of 98.7%, the rgSIFT descriptor with k-NN performed better than all other image descriptors and ML combinations. This highlights that feature–descriptor synergy plays a crucial role in ML-driven detection. The experimental findings also demonstrated how categorization

accuracy was impacted by non-overlapping region size. It was found that around the optimal non-overlapping region image size of 71 × 71 pixels, the classification accuracy drops with increasing or decreasing size. The suggested approach was simple to use for PV system inspection and played an essential role in carbon-free cities.

In 2023, Boubaker et al. [7] examined various ML and DL methods for PV module defect diagnosis and detection. Firstly, a set of infrared thermography images of both working and failing photovoltaic components was assembled. Second, the original dataset was split into two sub-datasets: the second sub-dataset had only faulty IRT images, whereas the first sub-dataset contained both faulty and normal IRT images. This controlled separation allowed for a more reliable assessment of binary and multi-class performance. The results showed that DL-based methods were more accurate in both binary and multiclass classification when it related to defect identification and diagnosis in PV modules/arrays. Indeed, it was discovered that DL methods were effective in accurately detecting and classifying various types of errors (98.71%). It was verified by a comparative analysis that DL-based methods performed better than ML-based models.

In 2024, Baltacı et al. [17] suggested a thermal image and inverter data analysis technique to efficiently monitor and maintain the electrical grid connection of renewable energy systems. This study introduces a hybrid data-fusion concept, merging visual and electrical features for more reliable diagnosis. In the same vein, refining the efficiency, dependability, and protection of PV systems was needed for early defect detection. Thermal imaging was demonstrated to be a profitable and effective inspection method. However, research showed that keeping a check on inverters in a solar farm could lower maintenance costs and increase output. Comprehensive analytics and data on each inverter, including voltage, current, temperature, and power, were necessary to maximize the efficiency of solar energy farms. Their goal in this work was to conduct two different fault evaluations using ML techniques with inverter and other physical data, and image processing techniques using thermal images. The outcomes demonstrated that these techniques may effectively identify hotspot and bypass failures on the panels.

(c) DL (CNN-based)

In 2021, Manno et al. [3] proposed a system that uses open-source frameworks to automatically classify thermographic images using a CNN. A variety of pre-processing techniques, such as Sobel Feldman, grey scaling, box blur filtering, thresholding, discrete wavelet transforms, pixel normalization and homogenization, have been evaluated to diminish image inaccuracy. These methods made it possible to categorize thermographic images taken with various tools and of varying quality without the need for certain procedures. The same approach produced 90% accuracy with a multi-layer perceptron architecture and 100% accuracy with a CNN on a dataset of 200 sectioned images. This large performance gap clearly illustrates the superiority of learned deep features over manually designed ones. In spite of providing an open alternative and an accurate tool that may be applied in any scientific area, the suggested method enhances the resolution of image categorization for distant failure detection situations.

In 2022, Zheng et al. [4]created an infrared PV image dataset using frame extraction processing and manual annotation of a publicly accessible video because there was no dataset of infrared PV panel images that was available to the public. This contribution is significant, as the lack of open datasets has long limited progress in the field. Consequently, the model had a detection speed of 49 f/s, a mAP of 98.1%, and 3.71 M parameters. Similarly, the YOLOv5's feature extraction component was changed for ShuffleNetv2's basic unit and the lighter focus structure. The original feature fusion technique was then made simpler. A comprehensive evaluation of each model's accuracy, detection speed, and model parameters revealed that the new model's indicators surpassed those of existing detection models, making it more appropriate for use on the UAV platform for real-time photovoltaic panel hot-spot fault detection.

In 2023, Wu et al. [6] implemented a technique termed SK-FRCNN, based on the Faster RCNN network to solve the issue of low detection accuracy in current models for hot spot detection on photovoltaic panels was presented for identifying hot spot faults on photovoltaic panels. This method represents an advanced extension of region-based frameworks tailored for multiscale hotspot detection. The faster RCNN network's feature extraction module enhanced its feature extraction performance by using an attention mechanism to adaptively modify the receptive field for hot spots of varying sizes. The pooling layer in the Faster RCNN model was replaced with the ROI align unit. By performing this, the quantization step was removed, and the bilinear interpolation method was used to produce floating-point pixel image values. This enhanced the hot spot identification localization accuracy and more accurately determined the ROI regions' feature representation. According to experimental data, the enhanced algorithm outperforms the original Faster RCNN network by 1.82%, achieving a 79.98% average detection accuracy for hot spot problems with solar panels.

In 2023, Duranay et al. [13] examined the possibility of employing DL to identify photovoltaic panel faults in infrared solar module images, which was an important step in improving the sustainability and efficiency of solar energy systems. This methodology used the Efficientb0 model. The NCA feature selector was used to choose 17,000 features from the exemplar model. The classification was completed using an

SVM classifier. When applied to a dataset with 12 classes, the proposed method produced excellent outcomes in terms of sensitivity, F1-score, precision, and accuracy metrics. These findings showed average values of 88.28% sensitivity, 91.50% precision, 89.82% F1-score, and 93.93% accuracy. The proposed method in this study correctly classified PV panel problems based on images of infrared solar modules. This hybrid DL–SVM design highlights the benefit of combining deep feature extraction with traditional ML classifiers.

In 2021, Ahmed et al. [14] developed ICNM from scratch to categorize PV panel infrared images according to their health, i.e., defective, hotspot, and healthy. In comparison to transfer obtained from pre-trained ShuffleNet, SqueezeNet and GoogleNet models, the ICNM has the lowest memory usage, the most straightforward architecture, a rapid execution time, and an accuracy of 96%. With 97.62% testing accuracy, ICNM is then reused using transfer learning to categorize PV panel flaws into five classes: horizontally aligned string, single, patchwork, bird drop, and block. This suggested method quickly and accurately identified and categorized the PV panels according to their condition and faults while using the least amount of system memory, reducing expenses on the PV investment. Its lightweight nature makes it suitable for embedded inspection systems.

In 2020, Herraiz et al.[15] presented a unique method for locating panels and identifying hotspots. A strong detection structure was created by combining two unique region-based CNNs. The primary contribution was the integration of telemetry and thermography data to produce a panel condition monitoring response. However, the fault detection during the examination was made possible by the automatic processing of the collected data. A thorough explanation of the methodology was given, including the various steps involved in creating neural networks, such as training, data collection and processing, and result generation. To verify the suggested methods, a thermographic examination of an actual photovoltaic solar plant was conducted. Statistical evaluation of the approach's accuracy, efficiency, and performance under several real-world settings produced good results. This study demonstrated the real-world viability of deep-learning-based inspection under operational plant conditions.

(ii) Based on Learning Approach

(a) Supervised Learning

In 2023, Li et al. [8] offered a method for detecting PV panel defects called GBH-YOLOv5. The BottleneckCSP module was developed to increase accuracy on multiscale targets by incorporating a prediction component for tiny target recognition to decrease tiny defect misses. This modification is especially important because small-scale defects often represent early-stage degradation that is difficult to detect with conventional architectures. To diminish the number of parameters and accelerate model inference, ghost convolution was employed. The creative image was first trimmed and flattened to physically enlarge the fault. After the processed images had been uploaded into GBH-YOLOv5, the depth features were obtained using the BottleneckCSP module, network processing based on Ghost convolution, and the prediction head of tiny targets. Ultimately, an FPN and a PAN structure were used to classify the collected characteristics. In the meantime, they verified the efficacy of the suggested approach by contrasting it with cutting-edge techniques. The mAP performance was at least 27.8% better using the suggested PV panel surface-defect detection network.

In 2022, Hong et al. [11] proposed an innovative framework to address the constraints for PV module flaws, which includes image acquisition, image segmentation, fault orientation, and defect warning. Using a dual infrared camera at low altitudes, images of the visible and infrared PV arrays were captured under identical conditions. This dual-modal acquisition strategy provides complementary information that enhances detection reliability. DL methods like the Deep ResNet algorithm and the fifth iteration of the YOLOv5 algorithm were presented under this framework. This method was able to adjust to almost every kind of lighting by combining defect location on infrared images with image segmentation from visible images. The results showed that using an infrared image labelled with the segmented area, this framework greatly boosts the speed of solar array separation to 36 images per second and the accuracy of defect identification to 95%.

In 2023, Bu et al. [12]developed a CNN-architecture-based technique for classifying PV cell faults that was trained on a series of infrared images. The lack of the initial dataset was addressed by using an offline data augmentation strategy to boost the network's capacity for generalization. This step ensured greater resilience of the model when applied to unseen field conditions. Throughout the experiment, assessment markers were used to quantify the outcomes achieved with four DL models to assess the efficacy of the models. The experiment demonstrated that the CNN model's fault classification accuracy was 97.42%, which was higher than that of the VGG 16, ResNet 18, AlexNet and current models. Furthermore, the suggested model had the best accuracy, quickest computation, and prediction speed. This approach demonstrated a great potential for use in automatic fault detection and classification that was capable of accurately identifying and classifying PV cell faults.

In 2022, Pathak et al. [18]developed two sophisticated CNN models. The first model's goal was to categorize the kind of fault impacting the panel, while the second model's work was to locate the faulty panel's region of interest. This two-stage strategy mirrors human inspection processes, thereby improving interpretability. When comparing several classification models using the F1 score as a criterion, the ResNet-50 transfer learning model achieves the highest score of 85.37% in the proposed method. The mAP assessment metric for object detection systems provided Faster R-CNN the highest score of 67%. The research proposed a method to reduce the amount of manual labour required for early fault localization and detection in solar panels.

In 2022, Tommaso et al. [19] suggested a unique automatic multi-stage approach that uses computer vision and the YOLOv3 network to identify panel flaws in aerial images taken by unmanned aerial vehicles. The model incorporates panel and defect detection to increase its accuracy, with an average inference time of 0.98 seconds for each image. This efficiency makes it practical for long-duration drone missions where thousands of panels must be analyzed. The proposed model was validated on two large PV plants in southern Italy with a noteworthy and exceptional AP@0.5 exceeding 98% for panel recognition, such as panel shading caused by soiling and bird dropping, and delamination. The model calculates the soiling coverage based on visual images and forecasts the severity of hotspot areas based on projected temperature gradients. Lastly, the impact of the various YOLOv3 output scales on the detection was examined.

In 2025, Ishak et al. [20] presented a new technique based on the 2TSS architecture specifically designed to improve hotspot detection in PV module thermal images. The model had two steps, which were the segmentation models with image pre-processing at the context, which was incorporated into the design of the suggested method. This hierarchical approach helps isolate subtle thermal anomalies that may not be visible in raw images. By comparing semantic models, this study improves understanding of multi-tier segmentation architectures in DL with an emphasis on performance optimization for solar energy systems. Three distinct segmentation models were evaluated: U-Net, ResNet 18, and ResNet 50. With 98% and 85% accuracy, respectively, the ResNet 50 showed excellent segmentation performance in both tiers. The suggested approach demonstrates a 2.26% gain in performance over the non-enhancing method when a combined improvement algorithm is used before training for hotspot segmentation.

(b) Semi-Supervised Learning

In 2023, Xia et al. [5] proposed the serrestandard model for the improvement process, which was based on the most recent research findings and the outcomes of simulating biological visual mechanism models in computer vision. In order to enhance the detection effect of surface flaws on solar panels, this model replicated the ventral visual pathway with an object detection model. The percolation-based image processing method for detecting visible fragments was used to determine the algorithm's position and the calculation results based on the improved standard model approach. It mostly refers to the MAX value that the C2 layer outputs, as well as the classification and detection outcomes regarding the presence of cracks and the completion of the crack-locating function. This hierarchical processing style enables the model to capture fine-grained structural irregularities that may be overlooked by fully supervised approaches. The experimental results showed that the recommended approach achieved an accuracy rate of 98.64% in testing and 98.86% in training, with neither the false detection rate nor the missed detection rate exceeding 1%. As a result, the suggested methods of the literature produced a high degree of accuracy, and that was also effective in identifying solar panel surface flaws.

(c) Meta-heuristic / Optimisation

In 2022, Usharani et al. [9] suggested the DL model with metaheuristic optimization for solar defect detection. Hyperparameter optimization was used in the development of MobileNetV2's learning model. Such optimization allows the model to achieve an optimal balance between accuracy and computational cost. The precision, F1-score, recall, and accuracy rates of the proposed model's performance are examined. The comparison of various methods of the PV fault-detection process is displayed in Table 1.

Table 1. *Comparison of various methods of the PV fault-detection process*

Category	Example Methods / Models	Description	Limitations	Future Scope
Classical Image Processing	MSER, Thermal Imaging Filters, Gaussian/Wiener filters	Locates hotspots and anomalies in PV thermal images using pixel-based heuristics, thresholding, and region detection.	• Varying outdoor conditions cause performance to decline. • Low automation and manual tuning. • Has difficulty with intricate fault patterns.	• AI-based adaptive thresholding through hybrid classical and DL filtering. • Environmentally sensible correction (adaptation to temperature and irradiance)
Shallow ML Techniques	k-NN, Naive Bayes, SVM with handcrafted features	ML models trained on manually extracted features (texture, thermal gradients).	• Feature engineering is necessary; generalization is restricted for defect types that are not yet visible. Sensitive to noise & camera discrepancies)	• Deep features plus hybrid features. • Pipelines for automatically extracting features. • Lightweight ML for edge and IoT deployment
DL (CNN-Based)	CNN, YOLO, Faster-RCNN, ResNet, MobileNet	Comprehensive learning for segmentation, detection, and classification from huge PV image datasets.	• Numerous annotated samples are needed. • The model's performance varies depending on the type of camera and climate. • There is a high computational demand.	• Swin Transformers: UAV + Edge-AI deployment and Vision Transformers (ViT). • Adaptation of domains to various solar areas
Semi-Supervised Learning	Serre model + LGBPHS, weak labels + CNN	Learns from both labelled and unlabeled PV images; this is helpful when there is a lack of labelled data.	• Pseudo-labels are necessary for accuracy. • May have difficulty with noisy infrared images	• Self-supervised/zero-shot learning; extensive unlabeled solar datasets. • Inadequate supervision (based on temperature maps or bounding boxes)
Meta-Heuristic / Optimisation-enhanced Models	Optimised MobileNetV2, Genetic algorithm-tuned DL	Uses optimisation and swarm intelligence to fine-tune deep models for increased accuracy and stability.	• A difficult tuning process. • Small datasets may be overfit. • Training time is high.	• NAS • Real-time evolutionary tuning. • Self-adaptive PV inspection software

4. Analysis and Discussion

This section explains the performance evaluation of various methods used in the solar panel hotspot failure detection process, including classical image processing, shallow ML techniques, DL, semi-supervised learning, and meta-heuristic/optimisation. These methods collectively reflect the evolution of PV fault detection from manual threshold-based techniques to highly automated intelligent diagnostic frameworks. Standard evaluation criteria, including accuracy, F1-score, precision, recall, specificity, sensitivity, mAP, IoU, and computational efficiency metrics, are used in the analysis. Fig. 1 displays the performance analysis of the various methods used in the solar panel hotspot fault prediction procedure. Based on the type of learning/processing category employed, the performance of the examined PV fault-detection models has been categorised.

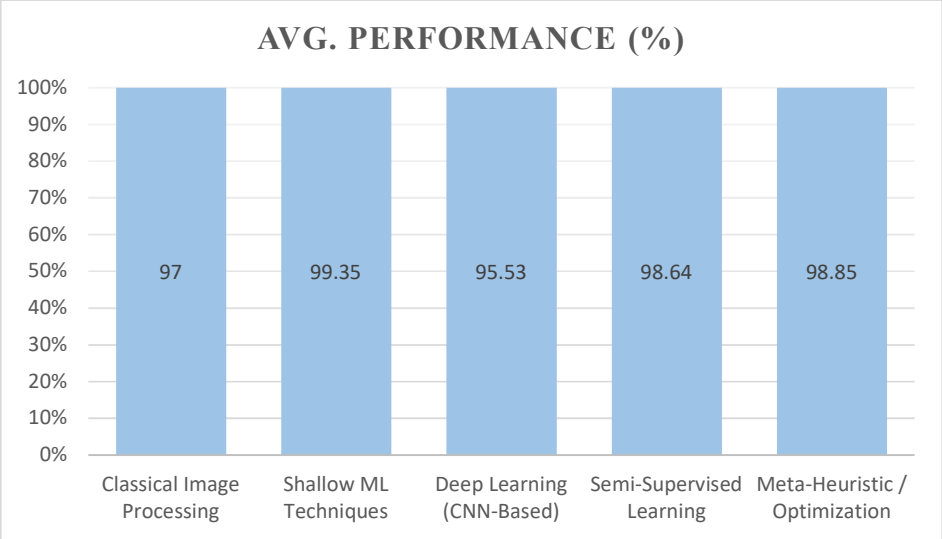


Fig 1. *Performance analysis of various methods used PV Fault-Detection process*

Fig. 1 shows that the shallow ML techniques obtained the highest average performance with the analysis of structured thermal datasets. CNN-based DL shows slightly lower average because some studies include complex UAV scenes and lightweight CNNs. Meta-heuristic improved the DL approaches perform exceptionally well, improving robustness. This improvement occurs because meta-heuristic algorithms efficiently search the hyperparameter space, enabling DL models to reach more optimal configurations. Classical imaging still performs well, but lacks scalability for large PV installations. Semi-supervised learning is emerging as a powerful technique, particularly when labelled IR datasets are scarce. Similarly, Table 2 lists the investigated papers that implemented the various approaches in the procedure of photovoltaic panel hotspot fault prediction.

Table 2. *Topology of Photovoltaic Panel Hotspot Fault Prediction Methods Using Image Processing Techniques*

Category	Sub-Category	Research papers
Based on the Processing Technique	Classical Image Processing	[2] [10]
	Shallow ML Techniques	[1][7][17]
	DL (CNN-based)	[3][4][6][13][14][15]
Based on Learning Approach	Supervised Learning	[8][11][12][18][9][20]
	Semi-Supervised Learning	[5]
	Meta-heuristic / Optimisation	[9]

5. Research Gaps and Future Directions

(i)Based on Processing Technique

(a) Shortcomings

- Highly sensitive to lighting, temperature and camera noise.
- These limitations often lead to inconsistent thermal signatures, making fault boundaries difficult to interpret across different inspection sessions.
- Requires large labelled datasets for training.
- Limited generalisation to different solar plants & climates.
- Models trained in one geographical region often fail when deployed elsewhere due to differences in irradiance levels, panel orientation, and dust accumulation patterns.
- Lower performance on complicated or mixed defects.
- Such defects may exhibit irregular shapes or overlapping thermal signatures, reducing detection accuracy in classical methods.

(b) Future Scope

- Intelligent pre-processing and adaptive thresholding.
- These techniques can help stabilise temperature gradients and minimise artefacts caused by varying ambient conditions.
- Transfer learning for solar-specific feature adaptability.
- Improved noise-robust & weather-adaptive imaging models.
- Explainable AI for reliable decision support in maintenance.

- This would enable technicians to understand the root cause of detected anomalies, enhancing trust in automated systems.

(ii)Based on Learning Approach

(a) Shortcomings

- Performance is sensitive to noise in thermal images.
- Internal reflections or uneven heating can confuse DL frameworks, resulting in misclassification or inaccurate bounding boxes.
- Requires certain labelled data to bootstrap the model.
- Computationally expensive optimisation cycles.
- Requires careful parameter tuning.
- Hyperparameters such as learning rate, batch size and augmentation strategy directly influence detection stability.

(b) Future Scope

- Active learning to intelligently label critical samples.
- This reduces annotation burden by allowing the system to request labels only for ambiguous or high-impact images.
- Zero-shot anomaly detection for unseen fault types.
- Real-time adaptive learning using evolutionary algorithms.
- Integration with digital-twin solar farms for predictive maintenance.
- Digital twins enable simulation-driven fault prediction and long-term defect evolution modelling.

6. Conclusion

In order to provide a thorough assessment of various image processing methods for PV panel hotspot defect prediction, this study observetwenty selected research papers. The review spans multiple methodological categories to capture the breadth of advancements made in the last five years. The concept and performance of each outcome are carefully analysed, with particular focus on measures such as accuracy, specificity, mAP, recall, F1-score, precision, sensitivity, IoU, and computational efficiency. The study examined different preprocessing and learning methods, including classical image processing, shallow ML techniques, DL, semi-supervised learning, meta-heuristic / optimisation-enhanced models and so on.

- A comprehensive assessment of computational choices was carried out, with an emphasis on computational sensitivity, complexity, prediction accuracy and specificity.
- This survey provided researchers with a roadmap for future research on solar panel hotspot fault prediction by defining specific future scopes.

Future research should concentrate on building hybrid AI models, integrating IoT for real-time monitoring, enabling predictive maintenance, and developing more standardised and reasonable alternatives in order to guarantee long-term optimal performance for photovoltaic panel hotspot defect prediction. Finally, increased collaboration between academia and industry will be essential for transitioning advanced detection frameworks into scalable field-ready solutions.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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