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Research Paper

Enhancing solar PV reliability with hybrid local features and infrared thermography

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ABSTRACT

The widespread adoption of Solar Photovoltaic Systems (PVS) faces challenges due to operational and environmental stresses, which can lead to hotspots and potential failures. This study introduces a novel hybrid local features-based approach for monitoring PVS using infrared thermographs. This method is designed to be resistant to scaling, noise, rotation, and haze. The approach involves subdividing each thermograph into 5 × 5 pixel grids, extracting features, and clustering them using an unsupervised algorithm to reduce memory usage. A shallow classifier is then employed, achieving an impressive 98 % training accuracy and 96.8 % testing accuracy with 5-fold cross-validation. Additionally, the model demonstrates high performance across various metrics, with precision values of 92 %, 100 %, and 100 %; recall values of 100 %, 100 %, and 90 %; and F1 scores of 0.958, 1.0, and 0.947 for the faulty, healthy, and hotspot classes, respectively. A Simulink model was developed to assess the impact of environmental stresses on PVS power losses, showcasing the method's practical applicability. This approach significantly enhances the reliability and performance of PVS, aligning with global initiatives such as the United Nations' Sustainable Development Goals, EU energy targets, the Kyoto Protocol, and the Paris Climate Accord. It ensures sustainable and reliable PVS operation over the next 25 years.

1. Introduction

Concerns over global warming and climate change have driven a significant shift towards green energy alternatives, particularly solar photovoltaics (PV) systems (Allouhi et al., 2022; Ahmed et al., 2021a). Unlike conventional power plants, which emit greenhouse gases (GHG) that contribute to global warming (Ahmed et al., 2021a), PV systems are environmentally friendly and have no stack emissions. They offer a global green energy potential of 1500–50,000 EJ per year, with the capability to supply 30–50 % of energy in competitive markets (Creutzig et al., 2017). Currently, over 3000 km^2 of the global area is covered by PV modules, which are the most prevalent form of solar power systems (Ilse et al., 2019). The power sector's average GHG emissions are 530gCO2eq/kWh, compared to the significantly lower 26–217 gCO2eq/kWh for solar energy (Ahmed et al., 2021a).

Despite their benefits, PV systems face challenges such as high capital costs and intermittent energy output, which affect their economic viability (Yin et al., 2020). The payback time of a PV system, which depends on its performance and lifespan, is crucial for its economic suitability (Huang and Yu, 2017). In China, PV power plants have faced penalties for intermittent energy supply, highlighting the need for reliable performance over a long lifespan, typically 25 years (Yin et al., 2020). Energy storage systems can mitigate intermittency issues, but external factors like environmental and operational stresses can still compromise PV system reliability, accelerate aging, and reduce their green energy potential (Ilse et al., 2019; Ahmed et al., 2021a; Hasan et al., 2022; Yang et al., 2024; Narasimman et al., 2023; Amiri et al., 2024; Abraim et al., 2023).

1.1. PV system losses

PV systems are designed to endure harsh climatic conditions, such as vibrations due to wind, extreme weather, and UV exposure (Amiri et al., 2024). However, they are susceptible to energy loss due to various external factors, including manufacturing defects, issues during transportation and installation, short circuiting, open circuit, partial shading, line-to-line fault, arc fault, bird droppings, soiling, module mismatch, environmental degradation, cell cracking, hail, snow, cracks, leakage current, interconnection failure, encapsulation degradation due to UV, rust, moisture penetration, and bypass diode failure (Ilse et al., 2019; Ahmed et al., 2021a; Yang et al., 2024; Narasimman et al., 2023; Amiri et al., 2024; Abraim et al., 2023; Yaichi et al., 2023; Triki-Lahiani et al.,

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2018; Osmani et al., 2023; Ali et al., 2020).

These defects significantly affect the performance of PV systems. For instance, soiling alone can reduce global power production by 4 %-7 %, leading to losses exceeding 4–7 billion euros annually (Ilse et al., 2019). Bird droppings, soiling, and shadows create localized hotspots, where PV cells operate in the reverse region, offering higher resistance to healthy cells connected in series. This causes current dissipation across the affected cells, creating hotspots (Ali et al., 2020; Ahmed et al., 2021b). If undetected, these issues can lead to permanent PV panel failures (Ahmed et al., 2021b). Literature reports an annual power loss of 18.9 %, with PV output limited to 50 % (Ali et al., 2020).

To ensure optimal performance, a fast, low-memory-requirement, and accurate monitoring system is essential (Ali et al., 2020; Ahmed et al., 2021b). Timely monitoring and classification of PV panels based on their health are crucial to avoid reliability and performance degradation (Ali et al., 2020). However, many faults and defects are not identifiable through visual inspection alone (Ahmed et al., 2021b). PV systems are generally monitored using two broad approaches: signal-based (voltage current characteristics, IV curves) and image-based (infrared thermographs, electroluminescence, photoluminescence) (Yang et al., 2024; Amiri et al., 2024; Osmani et al., 2023; Ali et al., 2020; Ahmed et al., 2021b; Sizkouhi et al., 2022; He et al., 2023). The infrared thermograph approach is widely used due to its non-invasive nature, low cost, simplicity, suitability for outdoor applications, real-time operation, user-friendliness, precision, accuracy, and speed (Ali et al., 2020; Ahmed et al., 2021b; Niazi et al., 2019).

1.2. Relevant studies

The literature has provided various approaches to monitor the health of PV panels to ensure optimal performance. Yang et al (Yang et al., 2024). proposed a conversion-based fast simulation model for IV curves to convert them into target ambient conditions as per IEC 60891–2021 for partial shading recognition and fault severity diagnosis for PV arrays. Narasimman et al (Narasimman et al., 2023). modeled a 5 MW grid-connected PV system using multiple artificial neural networks to identify the impact of various environmental parameters on PV generation. Amiri et al (Amiri et al., 2024). developed a PV model by extracting unknown parameters of a one-diode model under outdoor conditions using grey wolf optimization. They constructed an operational database through PSIM/MATLAB and used a random forest classifier for fault detection and diagnosis. Abraim et al (Abraim et al., 2023). introduced a PV soiling monitoring system to automate soiling data analysis and assist operations and maintenance teams in deciding on optimal cleaning dates.

Sizkouhi et al (Sizkouhi et al., 2022). developed RoboPV, a software package for autonomous aerial monitoring of PV plants, using an encoder-decoder with aerial images for optimal flight path planning and a neural network for fault detection. He et al (He et al., 2023). extracted multiple features from IV curves to diagnose PV abnormalities and compound faults through a multi-label classification method. Umair et al (Ali et al., 2022). employed the K-Nearest Neighbour (KNN) classifier to distinguish solar panels based on health using infrared thermographs. Ahmed et al (Ahmed et al., 2023). utilized pre-trained neural networks to extract features from PV panels exhibiting different faults and a healthy state, achieving high accuracy and fast response times.

Niazi et al (Niazi et al., 2019). extracted texture and HOG features, applied principal component analysis for dimension reduction, and used a Naive Bayes shallow classifier for PV panel health monitoring. Umair et al (Ali et al., 2020). improved this feature vector by combining HOG, RGB, LBP, and texture features, achieving high accuracy with shallow classifiers. Ahmed et al (Ahmed et al., 2022). extracted the strongest Gaussian features from PV infrared thermographs and used an unsupervised algorithm to categorize solar panels based on health conditions through shallow classifiers. Ahmed et al (Ahmed et al., 2021b). used multiple deep convolutional neural network models and transfer learning to diagnose PV panel health status.

Bhoopathy et al (Bhoopathy et al., 2018). presented a contactless photoluminescence-based approach for PV panel monitoring using sunlight as a radiance source. Kumar et al (Kumar and Maheshwari, 2021). generated new features based on voltage-current curve data and health-based information from electroluminescence image-based analysis. Berardone et al (Berardone et al., 2018). identified module defects using a combination of infrared and electroluminescence images. Wang et al (Wang et al., 2021). proposed a hybrid image processing and statistical machine learning approach to detect solar system anomalies through aerial thermography. Akram et al (Akram and Lotfifard, 2015). proposed a probabilistic neural network-based method to create a temperature-dependent relation for PV series resistance and ideality factor. Niazi et al., (2018) used texture features to classify solar panels into healthy and faulty categories using a Naive Bayes shallow classifier. Rouani et al (Rouani et al., 2021). used a data-driven methodology to identify partial shading in PV systems. Sarikh et al (Sarikh et al., 2021). proposed a fuzzy diagnostic algorithm based on electric signal measurements. Kapucu et al (Kapucu and Cubukcu, 2021). used a supervised heterogeneous ensemble model to detect normal and faulty states of PV systems.

Umair et al (Ali et al., 2024). proposed a global and local feature selection approach along with an improved Harris Hawks Optimization algorithm to enhance the efficiency of hotspot detection in PV systems using infrared imaging. Bu et al (Bu et al., 2024). utilized convolutional neural networks to analyze infrared images, identifying faults and classifying them with high accuracy to maintain the efficiency and safety of PV systems. Ukiwe et al (Ukiwe et al., 2024). applied transfer learning with a pre-trained VGG-16 model to identify hotspots with high accuracy, incorporating global average pooling and a SoftMax layer for efficient classification. Afrasiabi et al (Afrasiabi et al., 2024). proposed a novel approach to fault diagnosis in PV systems by leveraging multi-modal sensor data fusion and deep learning techniques to enhance the accuracy and robustness of fault detection. They combined data from various sensors and applied advanced deep learning models to improve the early detection of faults, ensuring better reliability and performance of PV systems. Nieto-Morone et al (Nieto-Morone et al., 2024). utilized visual inspection, electrical testing, electroluminescence imaging, and thermal imaging techniques to evaluate partially repaired PV modules. The authors used systematic categorization of defects and the assessment of their impact on power output and efficiency to develop strategies to increase the reuse of decommissioned modules and reduce environmental impact.

1.3. Contribution of the work

This study addresses several critical gaps in the current literature on PV system health monitoring. Existing image processing-based machine learning approaches for health and fault diagnosis are often limited to specific datasets and suffer from issues such as sensitivity to rotation, scaling, noise, blurring, and haze. These approaches also face trade-offs between memory usage and accuracy. Deep learning-based approaches, while powerful, have high computational complexity, memory and processing requirements, and are prone to underfitting and overfitting without strong datasets and careful hyperparameter tuning.

This research introduces a novel, fast, and simple machine learning-based health monitoring approach for PV systems. By dividing individual thermographs into 5×5 pixel grids and extracting hybrid local features that are invariant to scaling, rotation, haze, and noise, this study offers a robust solution to the limitations of existing methods. The use of an unsupervised clustering algorithm to downsize the feature vector addresses memory issues, while a shallow classifier Support Vector Machines (SVM) ensures fast training, validation, and testing with superior accuracy. This study has following contributions:

- The proposed method combines multiple feature extraction techniques to create a robust feature set that is resistant to common image processing issues.
- The use of unsupervised clustering to reduce the feature vector size is innovative and addresses memory constraints effectively.
- The approach achieves 98 % training accuracy and 96.8 % testing accuracy, demonstrating its effectiveness and reliability.
- The method's fast processing time makes it suitable for real-time monitoring of PV systems.

The proposed approach has significant implications for the renewable energy sector. By enhancing the reliability and performance of PV systems, it supports the broader adoption of solar energy, contributing to global sustainability goals. The method aligns with initiatives such as the United Nations' Sustainable Development Goals, EU energy targets, the Kyoto Protocol, and the Paris Climate Accord, ensuring the safe and reliable performance of PV systems over their 25-year service life.

2. Machine learning based health monitoring

Given the research gaps in health-based monitoring of PV panels, study propose a simple yet effective machine learning-based classification approach that addresses existing image processing issues. The proposed research methodology is illustrated in Fig. 1 and involves the following steps:

Data Acquisition: Infrared thermographs are acquired from a PV system using an infrared camera. These images capture the thermal profile of the PV panels, highlighting areas of potential concern.

Preprocessing: Each thermograph is assessed for quality. If a thermograph has background noise, is blurry, or has foreground issues, it is subjected to a dehazing algorithm, and the contrast is improved in the grayscale channel. Each thermograph is divided into 5 × 5 pixel sub-thermographs to facilitate detailed feature extraction.

Feature Extraction: Local features are extracted from each 5 × 5 pixel sub-thermograph. This step may result in some NaN/inf values and different feature vector lengths if the thermograph is not uniform in size. To resolve this issue, the 80 % strongest features are selected from each thermograph based on variance.

Clustering: To counter memory issues due to local features at the sub-thermograph level, an unsupervised clustering algorithm is applied. This clusters each thermograph's features into a refined feature vector of 300.

Classification: Shallow classifiers, such as SVM, are used to train the model on the feature vectors. A 5-fold cross-validation approach ensures proper model training.

Testing: A test vector from unseen thermographs is utilized to test the model's accuracy in classifying the PV panels into three health-based classes: healthy, hotspot, and faulty.

3. Proposed approach validation on a real-time PV system

3.1. Infrared thermographs

Infrared thermographs were captured from a 44.24 kW c-Si rooftop PV system located in Lahore, Pakistan. The PV system setup comprises 376 PV modules, each rated at 240 W. The system includes 8 strings, each containing 22 PV modules in series, making each string 5.28 kW (22 *240). These strings are connected to three inverters rated at 2x15kW and 10 kW. Two strings are connected to the 10 kW inverter, while the remaining strings are connected to the 15 kW inverters, with each inverter accommodating three strings. The infrared thermographs were captured under ambient temperatures ranging from 32° to 40°, a wind flow of 6.9 m/s, and an irradiance level of 700 W/m^2. A Pro 640 FLIR VUE system, which produces 8-bit depth thermal images with a spatial resolution of 640 × 512 pixels, was used for the infrared thermography. A detailed description of the experimental setup is provided in (Niazi et al., 2019).

3.2. Data preparation

The obtained thermographs were categorized into three health-based

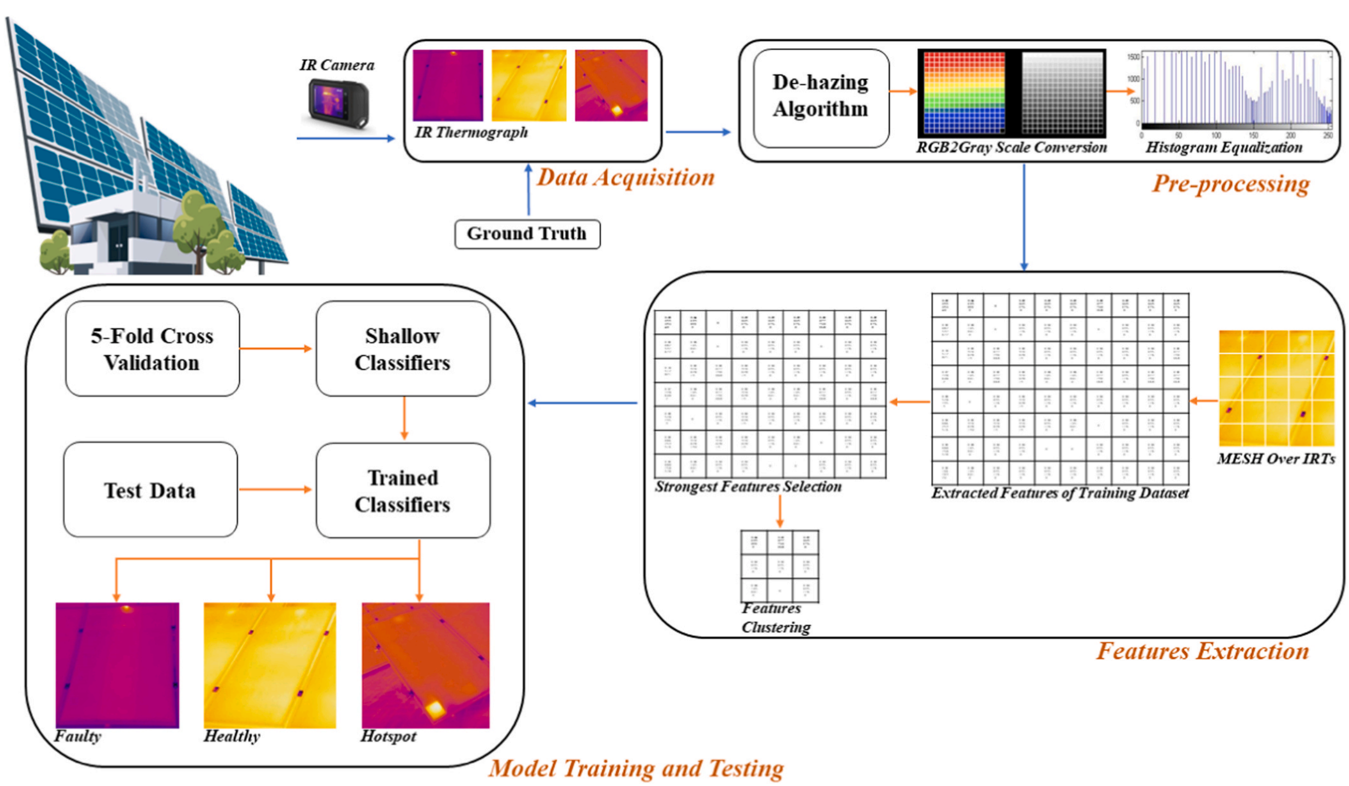


Fig. 1. Proposed methodology – simplified.

classes with the help of a field expert:

Healthy: Panels that are working perfectly fine based on patterns.

Hotspots: Panels suffering from hotspots due to environmental stresses, visible only through infrared thermography. Different types of hotspots, such as single cell, patchwork, string, and bird dropping, are considered in this class.

Faulty: Panels where more than one-third of the PV panel is under stress.

The dataset was further divided into two sub-datasets for training and testing models. This division was done randomly, with 80 % of the dataset reserved for training purposes and the remaining 20 % used to validate the trained model on unknown images. The images were split in equal proportions to ensure equal representation of each class in both training and testing.

3.3. Hotspot and faults visualization

To visualize the localized overheating caused by faults and hotspots (due to environmental issues such as bird droppings, etc.), different health-based states of the 44.24 kW PV system were binarized. Fig. 2 presents infrared thermographs and associated binarized images for impact analysis. The threshold selected for binarization of each thermograph is different and highly depends upon the texture. A black background represents healthy areas, and white represents localized heated points due to faults or hotspots. Improving the threshold will yield better results.

3.4. Features extraction

After acquiring the infrared thermographs, a de-hazing algorithm was applied to reduce misclassification issues that could arise due to the operation of PV panels in an open environment. Subsequently, the thermographs were converted into grayscale, and histogram equalization was applied to minimize the transformation of grayscale. The following steps were then performed:

Creation of Uniform Step Mesh: A 5 × 5 pixel uniform step mesh was created over the grayscale thermograph. This grid facilitates detailed feature extraction by dividing the thermograph into smaller, manageable sections.

Feature Extraction: Gaussian points through speeded-up robust (Bay et al., 2006) features were extracted from each 5 × 5 pixel window. Gaussian points are known for its invariance to scale and rotation, making it suitable for detecting features under varying conditions. Afterwards, nonlinear points through KAZE (Alcantarilla et al., 2012) features were also extracted from each 5 × 5 pixel window. Nonlinear points are in nonlinear scale spaces, providing robustness against scaling and rotation issues.

Feature Concatenation: The gaussian and nonlinear points extracted from each 5 × 5 pixel window were concatenated to form a comprehensive feature set. This combination leverages the strengths of both feature extraction methods, enhancing the robustness of the feature set.

Feature Selection: A total of 6125,232 features were extracted from the training dataset of thermographs. To increase classification accuracy and reduce storage capacity, the top 80 % variant points were retained. This selection was based on variance, ensuring that the most informative features were kept. NaN/inf values were removed from the features to ensure the integrity of the feature set.

Feature Reduction: The feature size was then reduced through unsupervised clustering using k-means, utilizing 300 clusters. The k-means clustering approach groups points based on resemblance into the same clusters, effectively reducing the dimensionality of the feature set while preserving its informative value. A feature vector was computed for each thermograph, with image class information; each feature vector comprised 301 features per image.

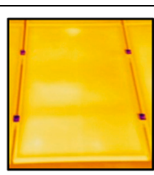
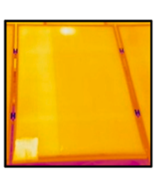
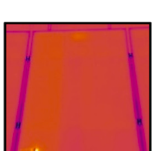
The proposed methodology ensures that the extracted features are robust, informative, and suitable for accurate classification of PV panel health states.

4. Proposed approach - results

The results of the proposed approach were processed using MATLAB 2022b on an Intel® Core™ i5–8th generation system with 8.0 GB RAM. The following steps and results were obtained:

- A total of 4537,584 of the strongest features were clustered using the k-means clustering algorithm. The final feature vector of 301 features per thermograph was then fed to shallow classifiers for training.
- The classifiers used included tree, SVM, linear discriminant (LD), K-NN, and naïve Bayes (nB).
- To prevent overfitting, a 5-fold cross-validation scheme was applied during training.

Table 1
PV health-based dataset (Niazi et al., 2019; Ahmed et al., 2022).

Health Status	IR Thermograph	Temperature	Dataset Size	Natural Degradation Cause	Operational degradation cause	Preventative maintenance
Healthy		50–60° C	32.38 %	Aging	-	Timely monitoring to avoid accelerated aging
Hotspot		65–80° C	31.43 %	Aging	Shadow of bird drops and vicinal objects	Cleaning through timely monitoring
Faulty		Above 80° C	36.19 %	Aging	Undetected prolonged hotspots	Replacement of module through timely monitoring

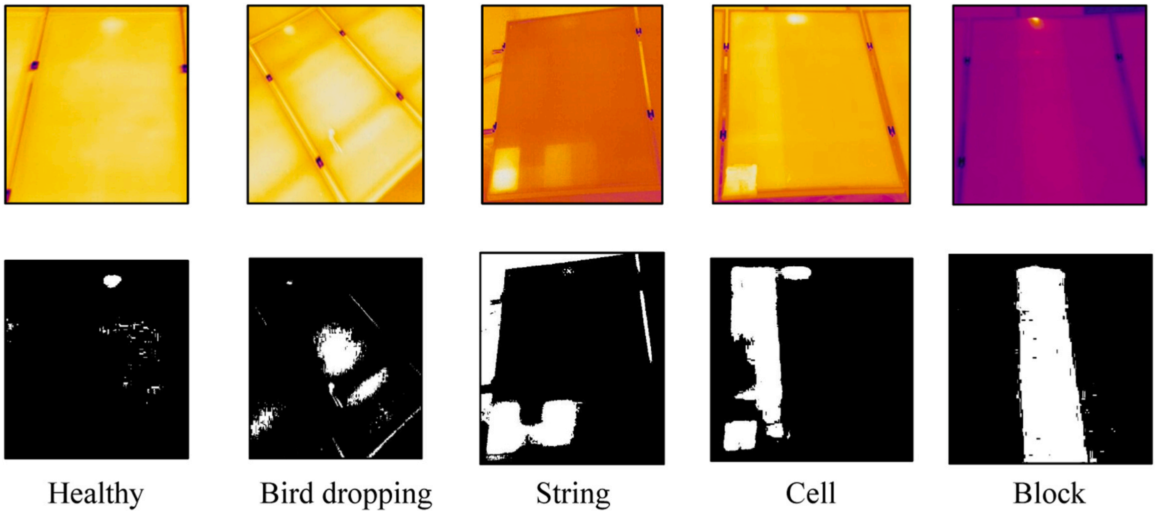


Fig. 2. Health states – Binarized.

- The accuracy metrics employed in both training and testing conditions included Positive Predictive Value (PPV), False Discovery Rate (FDR), False Negative Rate (FNR), and True Positive Rate (TPR). The results are presented in Table 2.

The training and testing accuracies are furnished in Table 3. The multi-class SVM achieved a training accuracy of 98 % with a prediction speed of 260 observations/sec and was trained in 43.18 seconds. This classifier was able to distinguish solar panels based on health and achieved a testing accuracy of 96.8 % when exposed to a new dataset. In contrast, the tree classifier resulted in an 86.9 % training accuracy with the least training time of 16.32 seconds among all classifiers and achieved a testing accuracy of 76.2 % when exposed to a new dataset.

Afterwards, additional parameters such as precision, recall, and F1 score were calculated for the SVM classifier (testing phase). The results showed precision values of 92 %, 100 %, and 100 %; recall values of 100 %, 100 %, and 90 %; and F1 scores of 0.958, 1.0, and 0.947 for the faulty, healthy, and hotspot classes, respectively. These results indicate that the SVM classifier performed exceptionally well, achieving high scores across all metrics. This suggests that the classifier was able to accurately distinguish between the different health states of the PV panels with high precision, recall, and F1 score.

Table 3
Classifiers training and testing accuracies.

Classifier	Training accuracy	Testing accuracy
Tree	86.9 %	76.2 %
LD	97.6 %	93.7 %
nB	92.5 %	92.5 %
SVM	98.0 %	96.8 %
K-NN	90.5 %	85.7 %

5. Discussion and findings

PV systems are increasingly being used as an alternative green energy solution to traditional energy production methods due to concerns about GHG emissions, environmental issues, and global warming. Despite their advantages and outdoor applications, PV systems are prone to various operational and environmental defects. These defects introduce reliability issues, reduce green energy output, increase payback time, and accelerate degradation rates. A single defective PV panel, due to its series connection, causes a power loss in the entire string.

To analyze the impact of such defects on PV system performance in real time, a PV model was developed in MATLAB/Simulink. This model consists of a string of 22 PV panels, each rated at 240 W, connected to a ramp DC load to focus on the losses within the PV panels. The characteristics of the PV panel are provided in Table 4. Three cases were created to analyze the PV system's performance:

Table 2
Accuracy metrics of shallow classifiers: Training and testing.

PV Class	Classifiers	TPR (%)		FNR (%)		PPV (%)		FDR (%)	
		Training	Testing	Training	Testing	Training	Testing	Training	Testing
Faulty	**Tree**	90.1	73.9	9.9	26.1	88.2	65.4	11.8	34.6
	LD	98.9	100	1.1	0	98.9	95.8	1.1	4.2
	nB	97.8	100	2.2	0	94.7	74.2	5.3	25.8
	SVM	98.9	100	1.1	0	100	92	0	8
	K-NN	97.8	100	2.2	0	93.7	79.3	6.3	20.7
Healthy	**Tree**	85.4	60	14.6	40	90.9	70.6	9.1	29.4
	LD	95.1	85	4.9	15	98.7	100	1.3	0
	nB	91.5	75	8.5	25	92.6	88.2	7.4	11.8
	SVM	96.3	100	3.7	0	98.8	100	1.2	0
	K-NN	84.1	70	15.9	30	88.5	93.3	11.5	6.7
Hotspot	**Tree**	84.8	95	15.2	5	81.7	95	18.3	5
	LD	98.7	95	1.3	5	95.1	86.4	4.9	13.6
	nB	87.3	55	12.7	45	89.6	73.3	10.4	26.7
	SVM	98.7	90	1.3	10	95.1	100	4.9	0
	K-NN	88.6	85	11.4	15	88.6	89.5	11.4	10.5

Table 4
PV panel datasheet.

Max power (P)	240 W
Voltage at MPP	23.16 V
Current at MPP	10.40 A
Open circuit voltage	26.71 V
Short-circuit current (Isc)	10.97 A
Temperature coefficient (Isc)	0.065 ± 0.015 %/ degC
Temperature coefficient (P)	−0.5 ± 0.05 %/ degC
Operating temperature	−40 – 85 degC

Healthy: Every PV panel operates at standard testing conditions (irradiance of 1000 W/m^2 at 25°C, as defined by IEC 61215–1–2021).

Minor Shadow or Soiling: A single panel's irradiance is reduced to 600 W/m^2, while the rest operate at 1000 W/m^2.

Cast Shadow: One-third of a PV panel has a cast shadow (0 W/m^2), while the rest are healthy.

The results showed that in both the hotspot and faulty cases, the PV system suffered significant power loss, as shown in Fig. 3. In the hotspot case, the affected PV cells were not producing Impp, leading to substantial power loss in the string. In the cast shadow case, although the affected panel was bypassed by diodes, long-term operation under such conditions can lead to bypass diode failure due to excessive current. Fig. 4 shows a minor current drop due to the active operation of bypass diodes.

Considering these issues, multiple artificial intelligence-aided approaches are provided in the literature to effectively distinguish solar panels based on faults and health status. Commonly used features like LBP, HOG, and texture have limitations related to rotation, scaling, memory, noise, and illuminance. Deep learning approaches, while powerful, require high memory, processing power, and strong datasets. To address these limitations, we proposed utilizing features invariant to scaling, rotation, and noise, combined with a de-hazing algorithm. The strongest points based on variance were extracted and clustered using k-means clustering. The proposed approach achieved 98 % accuracy on the training dataset and 96.8 % on the testing dataset. This method is robust against common issues and requires minimal memory. Table 5 compares different approaches from the literature (Ali et al., 2020, 2022; Ahmed et al., 2021b, 2023; Niazi et al., 2019, 2022) with our proposed method. Umair et al (Ali et al., 2022). achieved 98.66 % training accuracy with limitations, required a 71 × 71 non-optimal overlapped division, and was suitable for the K-NN classifier only.

6. Contribution to global green energy movements

Energy serves as the backbone of the modern era (Ahmed et al., 2021a). Therefore, the world has focused on green energy alternatives over conventional energy resources, considering their GHG emissions, climate change, and global warming potential. Several global movements and agreements emphasize the importance of transitioning to sustainable energy sources, including:

Kyoto Protocol: An international treaty that commits state parties to reduce GHG emissions, based on the scientific consensus that global warming is occurring and that human-made CO2 emissions are driving it (Kyoto Protocol To The United Nations Framework Convention On Climate Change).

Paris Climate Accord: An agreement within the United Nations Framework Convention on Climate Change (UNFCCC) dealing with GHG emissions mitigation, adaptation, and finance, starting in the year 2020 (The Paris Agreement).

European Union's 2030 and 2050 Targets: The EU has set ambitious targets to reduce GHG emissions by at least 40 % by 2030 and to become climate-neutral by 2050 (Renewable energy targets).

United Nations' Sustainable Development Goals (SDGs): A collection of 17 global goals designed to be a "blueprint to achieve a better and more sustainable future for all" (United Nations: Department of Economic and Social Affairs - Sustainable Development).

6.1. Contributions of the proposed approach

Ensuring Green Energy Output: The proposed approach ensures the PV system's green energy output over the next 25 years of service, even in the presence of environmental and operational stresses. This contributes to the reliability and sustainability of solar energy as a major green energy source.

Meeting UN's SDG 13: Climate Action: By ensuring the effective green energy contribution of PV systems, the proposed approach helps limit climate change. Reliable and efficient PV systems reduce reliance on fossil fuels, thereby decreasing GHG emissions.

Meeting UN's SDG 7: Affordable and Clean Energy: The approach promotes clean energy resources with no stack emissions. By improving the reliability and performance of PV systems, it makes solar energy a more viable and attractive option for energy production.

Meeting UN's SDG 9: Industry, Innovation, and Infrastructure: The approach promotes sustainable construction practices and fosters innovation in the field of renewable energy. By utilizing advanced machine learning techniques, it enhances the monitoring and maintenance of PV systems, contributing to the development of resilient infrastructure.

Supporting the Kyoto Protocol and Paris Climate Accord: The proposed approach aligns with the goals of the Kyoto Protocol and the Paris Climate Accord by reducing GHG emissions through the adoption of reliable and efficient PV systems. It supports global efforts to mitigate climate change and transition to sustainable energy sources.

Contributing to the EU's 2030 and 2050 Targets: By enhancing the performance and reliability of PV systems, the approach supports the EU's targets to reduce GHG emissions and achieve climate neutrality. It contributes to the broader adoption of solar energy, helping the EU meet its ambitious climate goals.

The proposed approach has significant implications for the renewable energy sector. By enhancing the reliability and performance of PV systems, it supports the broader adoption of solar energy, contributing to global sustainability goals. The method aligns with initiatives such as the United Nations' Sustainable Development Goals, EU energy targets, the Kyoto Protocol, and the Paris Climate Accord, ensuring the safe and reliable performance of PV systems over their 25-year service life.

By addressing the limitations of existing methods and providing a robust, efficient, and accurate approach to PV system health monitoring, this study contributes significantly to the field of renewable energy. The proposed method enhances the reliability and performance of PV systems, supporting their broader adoption and contributing to global sustainability goals.

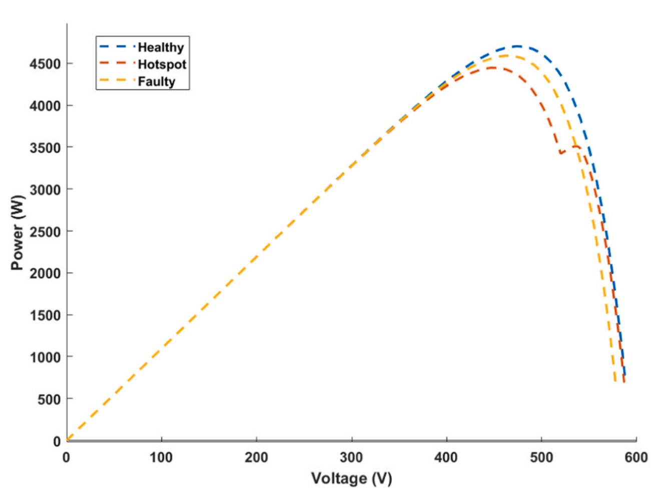


Fig. 3. Power voltage curve- Three cases.

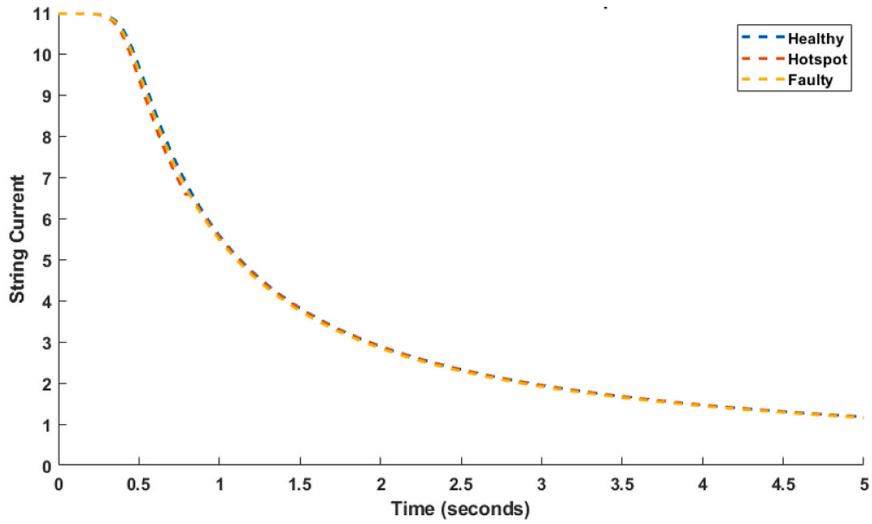


Fig. 4. Current status – Three cases.

Table 5
Proposed approach comparison with contemporary AI-based approaches.

Approach	Accuracy
Texture, HOG and PCA	94.10 %
Isolated CNN	96 %
RGB, LBP, mean HOG, and texture	96.80 %
Strongest SURF	97.60 %
Proposed	98 %
RB scale invariant feature transform	98.66 %,
Deep neural features (pre-trained network) and shallow classifier	97 %

7. Conclusion

This study introduces a novel hybrid local features-based approach for monitoring PV Systems using infrared thermographs. The proposed method effectively addresses several critical gaps in the current literature by offering a robust, efficient, and accurate solution for PV system health monitoring. By subdividing thermographs into 5 × 5 pixel grids and extracting hybrid local features, the approach demonstrates remarkable resistance to common issues such as scaling, noise, rotation, and haze. This robustness is further enhanced by using an unsupervised clustering algorithm, which significantly reduces memory usage without compromising accuracy.

The results of this study are particularly striking, with the method achieving a remarkable 98 % training accuracy and 96.8 % testing accuracy with 5-fold cross-validation. Additionally, the model's precision values of 92 %, 100 %, and 100 %; recall values of 100 %, 100 %, and 90 %; and F1 scores of 0.958, 1.0, and 0.947 for the faulty, healthy, and hotspot classes, respectively, indicate a high level of performance across these metrics. These high accuracy rates, combined with strong precision, recall, and F1 scores, underscore the reliability and effectiveness of the proposed approach. Furthermore, the fast processing time of the shallow classifier makes this method suitable for real-time monitoring of PV systems, ensuring timely detection and mitigation of potential issues.

Beyond its technical merits, the proposed approach has significant practical implications. By enhancing the reliability and performance of PV systems, it supports their broader adoption and contributes to global sustainability goals. This aligns with international efforts such as the United Nations' Sustainable Development Goals, EU energy targets, the Kyoto Protocol, and the Paris Climate Accord, ensuring the sustainable and reliable operation of PV systems over their 25-year service life.

In summary, the proposed hybrid local features-based approach significantly improves the monitoring and maintenance of PV systems, ensuring their optimal performance and longevity. This contribution is expected to have a substantial impact on the renewable energy sector, promoting the adoption of solar energy as a viable and sustainable alternative to conventional energy sources. By addressing the limitations of existing methods and providing a robust, efficient, and accurate solution, this study makes a significant contribution to the field of renewable energy and supports global efforts to mitigate climate change.

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CRediT authorship contribution statement

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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.

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Data availability

Data will be made available on request.

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