International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

A Review of Advanced Fault Diagnosis in Solar Panels: A Deep Learning approach

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ABSTRACT :

Solar panels play an essential role in the global transition toward clean and renewable energy, but their long-term efficiency and performance are heavily dependent on consistent monitoring and timely maintenance. Exposure to environmental factors such as adverse weather conditions, dust accumulation, high humidity, snow coverage, bird droppings, and physical impact gradually deteriorates the panels' ability to convert sunlight into electricity, often leading to reduced power output and increased maintenance costs if faults go undetected. To address these challenges, this project proposes an intelligent fault detection and classification system that harnesses the power of deep learning and advanced image processing to automate the inspection process, eliminating the limitations of manual monitoring. The system begins by analyzing high-resolution images captured by drones or surveillance cameras to distinguish between faulty and non-faulty solar panels, and once a fault is identified, it further classifies the issue into one of five specific categories — dusty panels, electrical damage, physical damage, snow coverage, or bird-drop contamination — each characterized by distinct visual patterns and structural symptoms. At the core of this system lies a Convolutional Neural Network (CNN), which excels in image recognition tasks by learning hierarchical features such as edges, textures, and spatial patterns, thereby enabling highly accurate classification of solar panel faults. To complement its predictive power with transparency, the model integrates Gradient-weighted Class Activation Mapping (Grad-CAM), which produces heatmaps overlaid on the original panel images, visually highlighting the exact regions that influenced the fault classification decision, thus fostering user confidence and aiding in maintenance planning. This combination of automated fault detection, clear visual explanation, and actionable maintenance recommendations transforms solar panel management into a proactive and efficient process, minimizing unexpected downtime, reducing inspection costs, and ultimately enhancing the reliability, lifespan, and energy output of both residential and industrial solar installations.

Key Words: Photovoltaic Systems, Image Processing, Deep Learning, Classification, Gradient-weighted Class Activation Mapping (Grad-CAM)

INTRODUCTION

Solar energy has emerged as one of the most promising and sustainable sources of renewable energy, with solar panels playing a pivotal role in harnessing sunlight and converting it into electricity. As the global demand for clean energy continues to rise, maintaining the performance and efficiency of solar panel installations has become increasingly crucial. Once installed, solar panels are subjected to a wide range of environmental stressors that can gradually degrade their efficiency and operational lifespan. Factors such as adverse weather conditions, the accumulation of dust, high humidity levels, and physical damage can compromise the overall functionality of the system, leading to reduced power output and increased maintenance costs.

Effective maintenance and timely fault detection are essential for ensuring that solar panels continue to operate at optimal levels. However, traditional manual inspection methods are time-consuming, labor-intensive, and prone to human error. To overcome these limitations, integrating advanced technologies such as machine learning and deep learning offers a more efficient and reliable solution. This project focuses on developing a robust classification system designed to identify and categorize faults in solar panels by leveraging cutting-edge image processing techniques and machine learning algorithms. The classification process begins by distinguishing between faulty and non-faulty solar panels through visual analysis of images. Faulty panels are then systematically categorized into five distinct types based on the nature of the damage:

- Dusty Panels: Accumulation of dust particles reduces sunlight absorption.
- Electrical Damage: Issues such as hotspots or defective connections lead to reduced efficiency.
- Physical Damage: Cracks or structural impairments compromise the panel's integrity.
- Snow-Covered Panels: Obstruction by snow prevents effective sunlight capture.
- Bird-Drop Contamination: Organic waste from birds hinders solar absorption.

To achieve high precision in fault identification, the system employs convolutional neural networks (CNNs), a subset of deep learning known for its powerful image recognition capabilities. CNNs excel at identifying complex patterns within images, enabling the system to classify the type of damage accurately. Moreover, the model provides actionable insights by offering potential solutions to mitigate or rectify the identified issues, allowing for timely maintenance and improved operational efficiency. By automating the fault detection process, this system significantly enhances the reliability and longevity of solar panel installations. It minimizes downtime, reduces manual inspection efforts, and optimizes energy output by addressing issues before they escalate. Ultimately, the integration of deep learning methodologies and image processing techniques in this project represents a transformative approach to maintaining and improving the performance of photovoltaic systems. Maintaining solar panels is essential for ensuring consistent energy output and operational longevity. Over time, environmental factors such as dust accumulation, adverse weather conditions, humidity, and physical damage can degrade panel efficiency. This project addresses these challenges by leveraging advanced image processing and deep learning techniques to detect and classify faults in solar panels.

Fig 1: Different Solar Panel images with faults

This project is designed to systematically leverage deep learning and web technologies for the identification and classification of faults in solar panels based on image data. The process begins with the acquisition of thermal and RGB images, along with metadata such as weather conditions, solar irradiance, and panel specifics, gathered from solar farms, drones, and open repositories. These images capture fault types like hotspots, cracks, dirt accumulation, and bypass diode failures, which are then cleaned, resized, normalized, and augmented using techniques like rotation, flipping, zooming, and brightness adjustment to ensure diversity and quality in the training dataset. Outlier detection using statistical methods ensures data consistency, while pre-trained Convolutional Neural Networks (CNNs) such as MobileNet, EfficientNet, and InceptionV3 are employed through transfer learning for feature extraction, enabling the model to adapt to the specific characteristics of solar panel faults. The dataset is strategically split into training, validation, and test sets to ensure robust evaluation, while the model undergoes iterative training and hyperparameter tuning with techniques such as early stopping and the Adam optimizer to optimize accuracy and prevent overfitting.

Once the model demonstrates satisfactory performance, it is deployed within a user-friendly web application built using HTML, CSS, JavaScript, and Flask, where users can upload panel images and receive instant diagnostic predictions, complete with fault type and confidence score. The system incorporates Grad-CAM visualizations to enhance model interpretability by highlighting image regions influencing the model's predictions, offering engineers valuable insights into fault locations. Additional data visualization tools like heatmaps and dynamic charts aid maintenance planning by presenting fault distribution trends and comparisons. Comprehensive testing — including unit, integration, and user acceptance testing — ensures the platform's reliability, while continuous monitoring, performance tracking with TensorBoard, and periodic retraining with new data uphold long-term model effectiveness. The combination of automation, explainability, and iterative maintenance makes this methodology both technically robust and practically valuable for real-world solar panel monitoring and fault diagnosis..

LITERATURE SURVEY

The authors primarily focus on developing a hybrid machine learning model to analyze energy potential and design a solar fault detection system for an AIoT-based solar-hydrogen system in a university setting. The paper employs machine learning algorithms (e.g., ensemble methods, deep learning) to optimize energy forecasting and detect faults like partial shading, cell cracks, and degradation in real time. The dataset includes solar generation logs, weather conditions (irradiance, temperature), and performance metrics from a university-based experimental setup. The research contributes to sustainable energy management by combining AI-driven analytics with renewable energy systems, offering a blueprint for smart solar-hydrogen hybrid infrastructures in academic and industrial settings [1].

The authors primarily focus on developing SPF-Net, a U-Net based deep learning model for solar panel fault detection using image classification techniques. The paper employs a modified U-Net architecture combined with image processing algorithms to identify various types of solar panel defects including cracks, hotspots, snail trails, and partial shading effects. The dataset consists of thermal and RGB images of solar panels collected from multiple photovoltaic farms, with annotations for different fault types and severity levels. The research contributes significantly to automated solar farm maintenance by providing a robust, computer vision-based solution that reduces reliance on manual inspection while improving fault detection reliability [2].

The authors primarily focus on developing a deep learning-based fault detection system for solar energy systems using convolutional neural networks (CNNs). The paper employs thermal and electroluminescence (EL) imaging techniques to capture solar panel defects, including microcracks, cell fractures, and potential-induced degradation. The dataset consists of high-resolution images collected from multiple solar farms, covering various panel types and environmental conditions. The methodology involves image preprocessing, feature extraction using CNN architectures, and fault classification with a focus on achieving high detection accuracy. The research contributes to automated solar farm maintenance by providing a scalable, deep learning-powered inspection system that improves reliability while reducing operational costs [3].

The authors primarily focus on developing a real-time image analysis system using MATLAB for solar panel fault detection with unmanned aerial vehicles (UAVs). The paper employs infrared (IR) and visual imaging techniques captured by drones to identify common photovoltaic faults, including hotspots, soiling, cell cracks, and partial shading. The dataset consists of aerial images collected from a 1MW solar power plant, with flights conducted at different times of day to capture varying thermal signatures. The methodology involves image acquisition, preprocessing, thermal analysis, and fault classification algorithms implemented in MATLAB's Image Processing Toolbox. The system's advantages include rapid inspection capability (10x faster than manual methods), cost-effectiveness compared to traditional techniques, and scalability for large-scale solar farms. The research contributes to automated solar farm maintenance by providing a practical, UAV-based inspection solution that reduces downtime and operational costs while improving fault detection reliability [4].

The authors primarily conduct a comprehensive review of deep learning methods for solar fault detection and classification, analyzing over 50 recent studies published between 2015-2020. The paper systematically examines various deep learning architectures including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models applied to both image-based and electrical parameter-based fault diagnosis in photovoltaic systems. The review also discusses preprocessing techniques including image augmentation, thermal image normalization, and electrical signal filtering that improve model performance. Future research directions emphasize the integration of digital twins with deep learning for predictive maintenance, development of lightweight models for edge deployment, and creation of standardized benchmark datasets for fair comparison of different approaches. The paper serves as a valuable reference for researchers by providing taxonomy of fault types, detailed comparison of deep learning architectures, and clear identification of current limitations in the field [5].

The authors primarily focus on conducting an in-depth evaluation of fault detection techniques in solar panels using advanced machine learning and deep learning methods. The study emphasizes the growing need for efficient fault diagnosis in photovoltaic (PV) systems to improve energy production and reduce maintenance costs. By analyzing performance data such as voltage, current, irradiance, and temperature from multiple solar farms, the paper explores the effectiveness of various algorithms, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Decision Tree Models (DTMs). Overall, the paper provides valuable insights into the current state of fault detection technologies, offering a detailed comparison of methodologies and emphasizing the importance of integrating data-driven approaches with practical deployment strategies for sustainable solar energy systems [6].

The authors primarily focus on investigating fault detection in solar photovoltaic (PV) panels caused by thermal effects, aiming to enhance the reliability and efficiency of solar energy systems. The study emphasizes that abnormal temperature variations in PV modules often lead to performance degradation, with faults such as hotspots, solder bond failures, and cell cracks being common issues. The research utilizes thermal imaging combined with machine learning techniques, including Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), to identify and classify these faults. The dataset comprises thermal images collected from solar farms under varying environmental conditions, capturing essential parameters such as surface temperature distribution, irradiance levels, and voltage fluctuations. Overall, the paper provides valuable insights into the importance of thermal effect analysis in solar PV systems, offering a comprehensive evaluation of current methodologies and highlighting the need for advanced fault detection technologies to ensure optimal solar energy production [7].

The authors primarily focus on developing an innovative transformer neural network for fault detection and classification in photovoltaic (PV) modules, aiming to enhance the efficiency and reliability of solar energy systems. The study highlights the limitations of traditional deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), in handling long-range dependencies and complex fault patterns. By leveraging the self-attention mechanism of transformer architectures, the proposed model excels at processing large-scale datasets and capturing intricate fault signatures in both image-based and electrical signal data. Overall, the paper offers valuable insights into the potential of transformer neural networks for advancing fault detection technologies, highlighting the need for scalable, accurate, and real-time diagnostic tools in the solar energy industry [8].

The authors primarily focus on conducting a comparative analysis of various machine learning techniques for fault detection in solar panel systems, with the objective of improving diagnostic accuracy and operational efficiency in photovoltaic (PV) installations. The study evaluates the performance of multiple machine learning models, including Support Vector Machines (SVM), Decision Tree Regressors (DTR), Random Forest (RF), and Artificial Neural Networks (ANN), in identifying and classifying common PV faults such as hotspots, partial shading, microcracks, and soiling effects. The dataset used comprises both electrical parameters (voltage, current, and power output) and image-based data (thermal and infrared images) collected from operational solar farms under varying environmental conditions. Key findings reveal that the Random Forest model demonstrated the highest overall accuracy (approximately 96%) for electrical fault classification due to its ensemble learning capability, while CNN-based models outperformed others in image-based fault detection, achieving an accuracy of over 97Overall, the paper provides valuable insights into the strengths and limitations of various machine learning models for fault detection in solar panels, serving as a useful reference for researchers aiming to improve the reliability and sustainability of solar energy systems [9].

The authors primarily focus on providing a comprehensive survey of photovoltaic (PV) panel overlay and fault detection methods, with the goal of analyzing current techniques and identifying research gaps to improve the reliability and efficiency of solar energy systems. The paper reviews a wide range of fault detection methodologies, including image-based analysis, electrical signal monitoring, infrared (IR) thermography, and hybrid machine learning approaches. It covers common PV faults such as hotspots, microcracks, delamination, potential-induced degradation (PID), partial shading, and soiling effectsOverall, the paper offers valuable insights into the state-of-the-art PV fault detection methods, serving as a crucial reference for researchers and practitioners seeking to enhance the reliability and efficiency of solar energy systems [10].

The authors primarily focus on developing an intelligent fault detection system for photovoltaic (PV) panels using neural networks, aiming to improve fault diagnosis accuracy and ensure the reliability of solar energy systems. The paper leverages advanced neural network architectures, including convolutional neural networks (CNNs) and multilayer perceptrons (MLPs), to detect and classify a wide range of PV faults such as hotspots, microcracks, delamination, partial shading, soiling, and potential-induced degradation (PID). The dataset used in the study consists of both electrical parameters (voltage, current, and power output) and image-based data (infrared and visible light images) collected from operational PV systems under different environmental conditions. The neural networks are trained on this diverse dataset to enhance fault detection performance across multiple fault types. Overall, the paper provides valuable insights into the application of neural networks for PV fault detection, offering a useful reference for researchers aiming to improve the reliability and efficiency of solar power systems [11].

The authors primarily focus on providing a comprehensive review of fault detection techniques and analysis methods for solar cells and photovoltaic (PV) modules, aiming to enhance the reliability and efficiency of solar energy systems. The paper systematically examines a wide range of fault detection methodologies, including visual inspections, thermal imaging, electroluminescence (EL), photoluminescence (PL), and electrical parameter analysis, alongside emerging approaches such as machine learning and artificial intelligence (AI) models. The study covers a broad spectrum of fault types, including hotspots, microcracks, potential-induced degradation (PID), delamination, soiling, corrosion, and partial shading, emphasizing their impact on the performance and lifespan of PV modules. Overall, the paper serves as a valuable resource by providing a detailed overview of existing fault detection methods, identifying key challenges, and suggesting potential research directions to improve the performance and longevity of PV modules [12].

The author primarily focuses on fault detection in photovoltaic (PV) systems, providing an in-depth analysis of various diagnostic techniques aimed at improving the reliability and efficiency of solar power generation. The paper explores a range of fault detection methods, including electrical parameter monitoring, thermal imaging, visual inspections, and data-driven analytical models. Key fault types discussed include hotspots, microcracks, soiling, corrosion, partial shading, and potential-induced degradation (PID), all of which significantly impact PV system performance and lifespan. Electrical parameter analysis, specifically the monitoring of current-voltage (I-V) characteristics and power output, is highlighted for its effectiveness in real-time fault detection and performance degradation analysis. The study emphasizes the importance of identifying deviations in parameters such as short-circuit current (I_sc), open-circuit voltage (V_oc), and fill factor (FF) to detect early-stage faults. Overall, this work provides a comprehensive overview of fault detection techniques in PV systems, outlining their advantages, limitations, and future research directions to enhance solar energy reliability and efficiency [13].

The authors primarily focus on the use of unmanned aerial vehicles (UAVs) integrated with infrared (IR) and visual image analysis for detecting fault conditions in solar modules at large-scale solar power farms. The study emphasizes the growing need for efficient, rapid, and non-invasive inspection methods to maintain optimal performance and reliability in photovoltaic (PV) systems. UAVs equipped with thermal and high-resolution visual cameras are deployed to identify various fault types, including hotspots, microcracks, delamination, corrosion, and partial shading. Overall, the study demonstrates the potential of UAVs as a transformative technology for solar module fault detection, offering a balance of efficiency, accuracy, and cost-effectiveness in large-scale PV systems [14].

The authors primarily focus on innovative approaches for forecasting and fault detection in residential solar electricity systems using advanced machine learning techniques. The study addresses the growing demand for efficient, reliable, and cost-effective solar energy solutions by integrating predictive analytics with fault detection methods to optimize performance and enhance system reliability. The paper explores multiple machine learning models, including support vector machines (SVM), long short-term memory (LSTM) networks, and convolutional neural networks (CNNs), to predict solar energy generation and identify system anomalies. The authors highlight the critical role of accurate forecasting in managing energy loads and preventing system downtime, with LSTM models achieving over 96% accuracy in predicting short-term power output. Overall, the study provides valuable insights into combining forecasting and fault detection to improve the reliability and efficiency of residential solar electricity systems, offering a promising direction for future research and practical implementation [15].

The authors primarily focus on fault detection in photovoltaic (PV) tracking systems using an image processing algorithm based on Principal Component Analysis (PCA) to enhance the efficiency and reliability of solar energy generation. The study addresses the critical issue of performance degradation in solar tracking systems caused by mechanical faults, alignment errors, and environmental factors such as dust accumulation and shading. By leveraging PCA, the proposed method simplifies complex image data into principal components, enabling the identification of anomalies by detecting deviations from normal operating conditions. The research utilizes high-resolution images captured by cameras installed on PV tracking systems, processing these images to detect structural misalignment, surface damage, and other mechanical faults. The authors highlight the advantages of using PCA for fault detection, including its ability to reduce dimensionality while retaining essential information, which significantly improves processing speed and efficiency. Overall, the study offers a practical and efficient approach to fault detection in PV tracking systems, demonstrating the potential of PCA-based image processing algorithms to improve the operational reliability and longevity of solar energy installations [16].

The authors primarily focus on developing an efficient fault classification method for solar panels using a novel deep learning architecture called Coupled UDenseNet. The study aims to address the growing need for accurate and real-time fault detection in photovoltaic (PV) systems to maintain optimal energy production and system reliability. By combining the strengths of U-Net and DenseNet architectures, the proposed model leverages dense connectivity and hierarchical feature extraction for precise fault classification. The paper offers valuable insights into leveraging advanced deep learning architectures for efficient and precise solar panel fault classification, contributing to the ongoing efforts to improve the reliability and performance of solar energy systems [17].

The authors primarily focus on developing an effective fault detection system for solar photovoltaic (PV) installations by integrating Support Vector Machine (SVM) algorithms with thermal image processing techniques. The study addresses the critical issue of performance degradation caused by common PV faults such as hotspots, delamination, microcracks, and partial shading, which often go undetected until they severely impact energy output. Thermal imaging is employed to capture temperature variations on PV modules, as abnormal heat patterns often indicate underlying faults. The collected thermal images are preprocessed to reduce noise and enhance fault visibility before being fed into the SVM classifier for fault identification. The research demonstrates that the SVM model achieves high classification accuracy (up to 95%) with minimal false positives, effectively distinguishing between healthy and faulty panels. The authors highlight the advantages of using SVM due to its robustness against small datasets, high generalization capability, and efficiency in handling non-linear fault patterns. The paper offers valuable insights into leveraging SVM and thermal imaging for accurate and reliable solar PV fault detection, contributing to more efficient maintenance and increased energy yield in renewable energy systems [18].

The authors primarily focus on developing an unsupervised fault detection and analysis system for large-scale photovoltaic (PV) installations using drones combined with machine vision technology. The study aims to overcome the limitations of traditional fault detection methods, which are often time-consuming, labor-intensive, and inefficient for large PV farms. By leveraging drones equipped with high-resolution infrared (IR) and visual cameras, the system automates the process of fault identification by capturing aerial imagery of PV modules. The machine vision approach utilizes image processing techniques to detect anomalies such as hotspots, cell cracks, delamination, soiling, and shading effects. Key advantages include scalability for large PV systems, reduced human intervention, and the ability to access hard-to-reach areas. Moreover, drones provide a non-invasive approach, allowing rapid and frequent inspections without disrupting PV operations. Future research directions include optimizing flight paths for energy-efficient drone operations, deploying real-time image processing for immediate fault alerts, and testing the system across different climatic conditions to evaluate robustness. The paper provides valuable insights into the potential of drone-based machine vision systems for enhancing the efficiency and accuracy of fault detection in large-scale solar PV installations [19].

The authors primarily focus on developing an advanced environmental fault diagnosis system for solar panels using solar thermal imaging combined with multiple convolutional neural networks (CNNs). The study addresses the challenges posed by environmental factors such as temperature fluctuations, dust accumulation, humidity, and partial shading, which significantly impact the performance and efficiency of photovoltaic (PV) systems. The proposed methodology involves capturing thermal images of solar panels under various environmental conditions and feeding the data into multiple CNN architectures for fault detection and classification. The system aims to differentiate between several fault types, including hotspots, cracks, delamination, and shading-induced performance degradation. To mitigate these limitations, the authors suggest integrating data augmentation techniques, optimizing CNN architectures for lightweight deployment, and incorporating other sensor data such as electrical parameters to improve diagnostic precision. Future research directions include developing energy-efficient models for real-time edge deployment, enhancing the robustness of fault detection under extreme weather conditions, and creating standardized datasets for benchmarking different deep learning methods. This study offers valuable insights for researchers and industry practitioners by showcasing the potential of deep learning-based thermal imaging systems in advancing environmental fault diagnosis for solar panels [20].

TABLE - I: ANAYLYSIS OF EXISTING METHODOLOGIES

Ref No.	Author Details & YOP	Techniques	Advantages	Limitations	Dataset Information
[1]	Joshua, S. R., Yeon, A. N., Park, S., & Kwon, K. (2024)	Hybrid Machine Learning combining AIoT	Integrates AIoT for real-time monitoring	Requires robust IoT infrastructure	University solar-hydrogen system data
[2]	Rudro, R. A. M., Nur, K., Al Sohan, M. F. A., et al. (2024)	SPF-Net: U-Net based deep learning	High accuracy in fault classification	Computationally intensive	High-resolution solar panel images
[3]	Duranay, Z. B. (2023)	Deep learning approach	Improves detection accuracy	Potential overfitting	Solar energy system dataset
[4]	Liao, K. C., & Lu, J. H. (2020)	MATLAB real-time image analysis using UAVs	Real-time monitoring; comprehensive coverage	Weather-dependent; UAV regulations	Solar panel UAV image dataset

[5]	Al-Mashhadani, R., Alkawsi, G., et al. (2021)	Review of deep learning methods	Comprehensive analysis of existing methods	No new techniques proposed	Various solar cells datasets
[6]	Nasr, M. F., Mohsen, M., & Elberry, A. (2024)	Thermal Imaging	Effective fault detection in thermal conditions	Affected by environmental factors	Thermal images of solar panels
[7]	Ramadan, E. A., Moawad, N. M., Abouzalm, B. A., ... (2024)	Transformer Neural Network	High fault classification accuracy	Requires high computational power	Photovoltaic module datasets
[8]	Abdelsattar, M., AbdelMoety, A., & Emad-Eldeen, A. (2024)	Machine Learning Techniques	Effective for comparative analysis	Model tuning complexity	Various solar panel datasets
[9]	Yang, C., Sun, F., Zou, Y., ... (2024)	Survey of PV fault detection methods	Comprehensive coverage of techniques	Generalized results	Multiple PV system datasets
[10]	Bouzidi, M., Rahmoune, M. B., & Nasri, A. (2024)	Neural Networks	Intelligent fault detection	Overfitting in small datasets	PV panel dataset
[11]	Bouzidi, M., Rahmoune, M. B., & Nasri, A. (2024)	Neural Networks	Accurate fault detection with minimal human intervention.	High computational cost.	Dataset of solar panel images with fault annotations.
[12]	Singh, D., & Kathuria, R. S. (2018)	Various fault detection techniques (IR imaging, EL imaging)	Comprehensive review helping in selecting suitable methods.	Lacks practical implementation insights.	Compilation of existing datasets for PV fault detection.
[13]	Nilsson, D. (2014)	Signal processing and real-time monitoring	Real-time detection capability.	Limited to small-scale PV systems.	Simulation data from PV test systems.
[14]	Liao, K. C., & Lu, J. H. (2021)	IR and visual image analysis using UAVs	Efficient fault detection in large solar farms.	Affected by weather conditions.	Dataset of UAV-captured IR and visual images.
[15]	Kalra, S., Beniwal, R., Singh, V., & Beniwal, N. S. (2024)	Machine Learning for Forecasting and Fault Detection	Improves energy efficiency by early fault detection.	Requires large datasets for training.	Dataset of residential solar panel performance metrics.

[16]	Amaral, T. G., Pires, V. F., & Pires, A. J. (2021)	Image Processing using PCA	Effective in identifying misalignment issues.	Limited to specific fault types.	Image dataset of PV tracking systems.
[17]	Pamungkas, R. F., Utama, I. B. K. Y., & Jang, Y. M. (2023)	Coupled UDenseNet for classification	High accuracy in fault classification.	Requires powerful hardware.	Dataset of solar panel fault images.
[18]	Natarajan, K., Bala, P. K., & Sampath, V. (2020)	SVM and Thermal Image Processing	Efficient in thermal fault detection.	Performance drops with noisy data.	Thermal image dataset of PV systems.
[19]	Alsafasfe,M., Abdel-Qader, I., Bazuin, B., Alsafasfeh, Q., & Su, W. (2018)	Machine vision with drones	Covers large PV systems quickly.	Susceptible to environmental interference.	Drone-captured PV system images.
[20	Selvaraj, T. Rengaraj, R.Venkatakrishnan, etal. (2022)	Multiple CNNs with thermal imaging	High fault detection accuracy.	High computation and maintenance cost.	Thermal image dataset from solar panels.

3. CONCLUSION

The proposed faulty solar panel detection system integrates deep learning-based classification with an interactive web interface, enabling accurate fault identification and interpretability through Grad-CAM visualizations. By leveraging MobileNet for real-time classification, the system achieves an optimal balance between accuracy and computational efficiency, making it suitable for both large-scale solar farms and household applications. Comparative analysis with ResNet-50 and VGG16 highlights MobileNet's advantages in terms of speed and lightweight architecture while maintaining competitive accuracy. The heatmap visualizations generated by Grad-CAM provide transparency to the decision-making process, reinforcing trust in the model's predictions. The experimental results demonstrate that the system effectively categorizes solar panel faults, including dust accumulation, electrical damage, physical cracks, snow coverage, and bird droppings, with high confidence levels. The user-friendly web-based interface allows for seamless image uploads, instant predictions, and visual explanations, making it an accessible tool for non-experts. Furthermore, the incorporation of severity and urgency ratings enables informed decision-making regarding maintenance priorities. While the system performs well in controlled conditions, future improvements will focus on expanding the dataset, enhancing model robustness against varying environmental conditions, and integrating additional explainability techniques for improved reliability. By addressing these aspects, the system can further contribute to the sustainable maintenance and efficiency optimization of solar energy infrastructure. In addition, incorporating temporal analysis and historical tracking of panel faults could provide predictive maintenance capabilities, allowing for the anticipation of potential failures before they escalate. Integrating Internet of Things (IoT) sensors and real-time data streams with the system may further enhance its utility by enabling continuous monitoring without manual intervention. Collaborations with solar farm operators and domain experts can also refine the categorization schema, ensuring that the system remains aligned with industry standards and practical requirements.

Ultimately, the proposed solution represents a step forward in intelligent energy management, combining technological sophistication with user accessibility. As solar energy adoption continues to rise globally, such intelligent diagnostic tools will play a pivotal role in minimizing power losses, reducing maintenance costs, and promoting the long-term sustainability of clean energy systems.

REFERENCES

[1]. Joshua, S. R., Yeon, A. N., Park, S., & Kwon, K. (2024). A Hybrid Machine Learning Approach: Analyzing Energy Potential and Designing Solar Fault Detection for an AIoT based Solar–Hydrogen System in a University Setting. Applied Sciences, 14(18), 8573.

[2]. Rudro, R. A. M., Nur, K., Al Sohan, M. F. A., Mridha, M. F., Alfarhood, S., Safran, M., & Kanagarathinam, K. (detection using U-Net based deep learning image classification. Energy Reports, 12, 1580-1594. 2024). SPF-Net: Solar panel fault.

[3]. Duranay, Z. B. (2023). Fault detection in solar energy systems: A deep learning approach. Electronics, 12(21), 4397.

[4]. Liao, K. C., & Lu, J. H. (2020, April). Using Matlab real-time image analysis for solar panel fault detection with UAV. In Journal of Physics: Conference Series (Vol. 1509, No. 1, p. 012010). IOP Publishing.

[5]. Al-Mashhadani, R., Alkawsi, G., Baashar, Y., Alkahtani, A. A., Nordin, F. H., Hashim, W., & Kiong, T. S. (2021). Deep learning methods for solar fault detection and classification: a review. solar cells, 11, 12.

[6]. Dhanraj, J. A., Mostafaeipour, A., Velmurugan, K., Techato, K., Chaurasiya, P. K., Solomon, J. M., ... & Phoungthong, K. (2021). An effective evaluation on fault detection in solar panels. Energies, 14(22), 7770.

[7]. Nasr, M. F., Mohsen, M., & Elberry, A. (2024). Solar Photovoltaic Panels Fault Detection Due to Thermal Effects. Journal of International Society for Science and Engineering, 6(2), 26-35.

[8]. Ramadan, E. A., Moawad, N. M., Abouzalm, B. A., Sakr, A. A., Abouzaid, W. F., & El-Banby, G. M. (2024). An innovative transformer neural network for fault detection and classification for photovoltaic modules. Energy Conversion and Management, 314, 118718.

[9]. Abdelsattar, M., AbdelMoety, A., & Emad-Eldeen, A. (2024). Comparative Analysis of Machine Learning Techniques for Fault Detection in Solar Panel Systems. SVU-International Journal of Engineering Sciences and Applications, 5(2), 140-152.

[10]. Yang, C., Sun, F., Zou, Y., Lv, Z., Xue, L., Jiang, C., ... & Cui, H. (2024). A Survey of Photovoltaic Panel Overlay and Fault Detection Methods. Energies, 17(4), 837

[11]. Bouzidi, M., Rahmoune, M. B., & Nasri, A. (2024). Intelligent fault detection of photovoltaic panel using neural networks. Studies in Engineering and Exact Sciences, 5(1), 3161-3177.

[12]. Singh, D., & Kathuria, R. S. (2018). Fault detection techniques and analysis of solar cells and PV modules: A review. Journal of Energy and Economic Development, 3(2), 41-48.

[13]. Nilsson, D. (2014). Fault detection in photovoltaic systems.

[14]. Liao, K. C., & Lu, J. H. (2021). Using UAV to detect solar module fault conditions of a solar power farm with IR and visual image analysis. Applied Sciences, 11(4), 1835.

[15]. Kalra, S., Beniwal, R., Singh, V., & Beniwal, N. S. (2024). Innovative Approaches in Residential Solar Electricity: Forecasting and Fault Detection Using Machine Learning. Electricity, 5(3), 585-605.

[16]. Amaral, T. G., Pires, V. F., & Pires, A. J. (2021). Fault detection in PV tracking systems using an image processing algorithm based on PCA. Energies, 14(21), 7278.

[17]. Pamungkas, R. F., Utama, I. B. K. Y., & Jang, Y. M. (2023). A Novel Approach for Efficient Solar Panel Fault Classification Using Coupled UDenseNet. Sensors, 23(10), 4918.

[18]Natarajan, K., Bala, P. K., & Sampath, V. (2020). Fault detection of solar PV system using SVM and thermal image processing. Int. J. Renew. Energy Res, 10(2), 967-977.

[19]. Alsafasfeh, M., Abdel-Qader, I., Bazuin, B., Alsafasfeh, Q., & Su, W. (2018). Unsupervised fault detection and analysis for large photovoltaic systems using drones and machine vision. Energies, 11(9), 2252.

[20]. Selvaraj, T., Rengaraj, R., Venkatakrishnan, G., Soundararajan, S., Natarajan, K., Balachandran, P., ... & Selvarajan, S. (2022). Environmental fault diagnosis of solar panels using solar thermal images in multiple convolutional neural networks. International Transactions on Electrical Energy Systems, 2022(1), 2872925.