



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 7, July 2025

Advanced Fault Diagnosis in Solar Panels: A Deep Learning approach

Dr. V. Vasudha Rani, Ravindra Turpati

Associate Professor, Department of Information Technology, GMRIT, Rajam, India

Department of Information Technology, GMRIT, Rajam, India

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 (GradCAM), 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.

KEYWORDS: Photovoltaic Systems, Image Processing, Deep Learning, CNN, Classification, Grad-CAM

I. 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.



Figure 1: Solar Panels

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 a critical aspect of ensuring stable energy generation and extending the operational lifespan of photovoltaic systems. However, the performance of solar panels is highly susceptible to environmental stressors such as dust accumulation, adverse weather conditions, high humidity, temperature fluctuations, and physical damage caused by external forces. These factors can progressively degrade the energy output of the panels, leading to increased maintenance costs and reduced efficiency.

To address these challenges, this project integrates advanced image processing techniques with deep learning methodologies to automate the fault detection and classification process. Image processing plays an essential role in preparing the input data for the deep learning model by refining, enhancing, and segmenting images to expose subtle features and patterns that indicate faults. detection and preventive healthcare.

II. LITERATURE SURVEY

A. Introduction

Several researchers have proposed diverse methodologies for fault detection and classification in solar panels, leveraging advanced image processing and deep learning techniques to ensure reliable performance. These existing studies focus on real-time insights, emphasizing performance metrics such as accuracy, precision, and recall. The literature explores a wide range of approaches, each with distinct technologies, advantages, and limitations, along with the datasets required for effective implementation. This section provides a comprehensive review of previous works related to solar panel fault detection. It highlights the methodologies adopted, the benefits they offer in terms of fault classification accuracy, and the challenges they face in real-world applications. By analyzing these existing studies, this literature survey aims to identify gaps and inspire innovative solutions by providing strong findings and limitations of the existing works and developments in these relevant fields, so that these can be used to enhance the reliability and lifespan of solar panel installations.

B. Existing Methodologies

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 97. Overall, 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 effects. Overall, 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].

III. METHODOLOGY

This work presents a comprehensive machine learning pipeline that integrates key components such as data acquisition, preprocessing, feature engineering, model training, evaluation, visualization, and web application development for deployment in a real-world scenario. Specifically applied to solar panel fault diagnosis, the methodology, depicted in Figure 2, combines traditional machine learning steps with deep learning-based image analysis to enhance the detection of faults in solar energy systems. The pipeline begins with the systematic collection of a diverse and representative image dataset covering multiple fault categories such as dusty, snow-covered, bird drop, clean, electrical damage, and physical damage. Preprocessing steps, including image resizing, normalization, and augmentation, are employed to improve generalization and reduce overfitting. Feature engineering is conducted where necessary, although deep learning models largely handle automatic feature extraction.

Model training involves the use of convolutional neural networks (CNNs), leveraging their capacity to learn spatial hierarchies of features directly from raw image pixels. These models are optimized using backpropagation and stochastic gradient descent, with performance assessed through metrics like accuracy, precision, recall, F1-score, and confusion matrix analysis. In addition to quantitative evaluation, interpretability is addressed through visualization techniques such as Grad-CAM, enabling identification of image regions that most influenced the model's predictions.

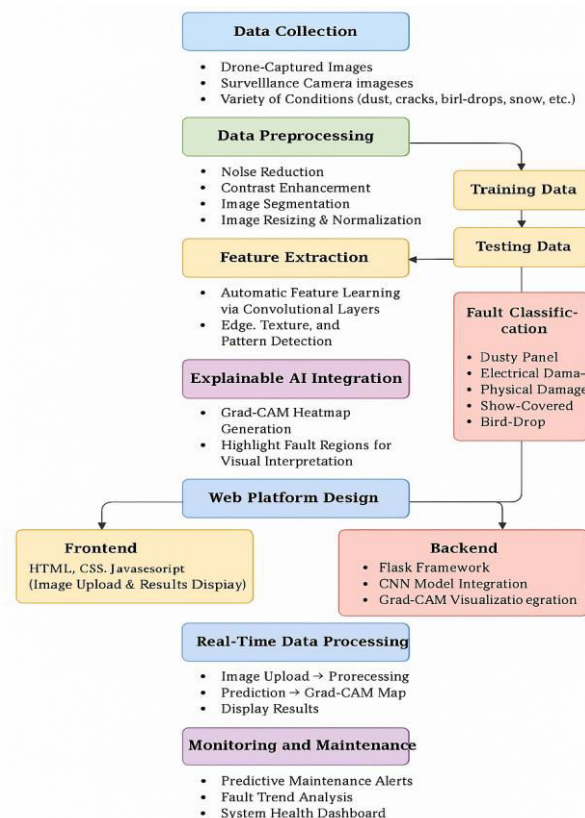


Figure 2: Flow of operations

Following validation, the trained model is encapsulated within a Flask-based web application, facilitating real-time image upload and fault analysis for end-users. The frontend displays not only the predicted fault type and confidence score but also contextual insights such as severity, urgency, recommended maintenance action, and heatmap-based localization of affected areas. This ensures that the system is not only technically accurate but also operationally useful for technicians and field engineers. Ultimately, this end-to-end pipeline bridges advanced AI techniques with practical solar farm monitoring, offering a scalable and intelligent solution to maintain the efficiency and longevity of photovoltaic systems

A. Data Acquisition and Preprocessing

The initial stages, data acquisition and preprocessing form the backbone of the project, focusing on collecting a diverse and representative dataset composed of thermal and RGB images, each offering distinct diagnostic value: thermal images reveal heat-related anomalies like hotspots and open circuits, while RGB images highlight surface issues like dirt, cracks, and delamination. This multi-modal image data is further enriched with metadata such as weather conditions, irradiance levels, and panel age to provide contextual depth during model training. Fault categories are clearly defined into six major types including hotspots, cracks, delamination, dirt and dust accumulation, bypass diode faults, and a normal (no fault) class, ensuring structured labeling for supervised learning. Preprocessing, a critical step before model ingestion, includes data cleaning to remove corrupted and duplicate images and address missing metadata through imputation. Image resizing to 224x224 pixels ensures compatibility with deep learning architectures like MobileNet and EfficientNet, while normalization of pixel values improves computational efficiency and training stability. Augmentation strategies like flipping, rotation, zooming, and brightness adjustment are employed to create a diverse dataset that enhances model generalization. Additionally, outlier detection through methods such as Z-score and IQR helps identify erroneous sensor readings or extreme pixel values in thermal images, preserving the dataset's quality. Together, these steps build a robust foundation that supports reliable, scalable, and efficient fault diagnosis in solar panel systems, ultimately improving energy output and system longevity through intelligent image-based analysis and user-friendly deployment via web interfaces.



Figure 3: Collection of faulty solar panels

B. Feature Extraction and Data Splitting

This section outlines the combined processes of feature extraction, engineering, and data splitting, which are essential for transforming raw image data into structured inputs suitable for deep learning models. To enhance fault detection in solar panels, transfer learning was employed using pre-trained Convolutional Neural Networks (CNNs) such as MobileNet, Inception V3, and EfficientNet. These architectures are particularly effective for visual data due to their ability to learn hierarchical features—starting from low-level patterns like edges to high-level object structures. By leveraging the learned representations from large-scale datasets like ImageNet, the lower layers of these networks were retained while the final layers were adapted to the specific classification tasks relevant to solar panel faults. This approach significantly reduced training time, improved generalization, and minimized the need for extensive labeled data. After extracting the necessary features, the dataset was divided into three parts: 70% for training, 15% for validation, and 15% for testing. The training set facilitated model learning, the validation set supported hyperparameter tuning and overfitting control, and the test set provided an unbiased assessment of performance. This systematic data

handling process ensured consistency and reliability in the final evaluation of the model, enabling confident deployment in real-world solar panel monitoring systems.



Figure 4: Data splitting

C. Model Training and Evaluation

Model development for solar panel fault diagnosis was carried out using MobileNet as the base architecture. The lower layers of the network were kept frozen to preserve generic visual features learned from large-scale datasets, while the top layers were retrained to adapt to domain-specific characteristics of solar panel faults. Additional dense layers with ReLU activation were integrated to capture non-linear relationships in the extracted features. To improve generalization, hyperparameters were carefully tuned through experimentation. Learning rates ranging from 0.001 to 0.0001 were tested to achieve stable convergence. Batch sizes of 16, 32, and 64 were evaluated to identify the best balance between training efficiency and model accuracy. The Adam optimizer was chosen for its adaptive learning capability, and categorical cross-entropy loss was employed to address the multi-class classification nature of the task. To avoid overfitting, early stopping was implemented by monitoring validation accuracy. Once trained, the model underwent a thorough evaluation process. Accuracy was used as the primary metric to gauge overall correctness, while precision and recall offered insights into the model's fault identification reliability. The F1-score provided a harmonic mean of these two metrics, helping assess the trade-off between false positives and false negatives. A confusion matrix was generated to visualize classification performance across different fault categories, revealing any misclassifications. Additionally, the Receiver Operating Characteristic (ROC) curve was analyzed to understand how the model performs under varying thresholds, helping confirm its robustness and suitability for deployment in real-world monitoring environments.

D. Web Application Development and Visualizations

To ensure accessibility and usability of the trained solar panel fault detection model, we developed a web application that facilitates direct user interaction. The system allows users to upload panel images and receive real-time predictions regarding fault type and confidence score. The frontend, built using HTML, CSS, and JavaScript, provides a responsive and user-friendly interface compatible with both desktop and mobile platforms. On the backend, Flask manages model communication, handles API requests for image upload, and processes data through the deep learning pipeline. The application's design emphasizes simplicity and efficiency—users submit images, the server runs inference using the trained model, and the results are rendered with clear visual indicators. In parallel, we implemented data visualization tools to enhance interpretability. Visualization modules developed using Matplotlib and Plotly present insights such as fault distribution, detection frequency, and model performance metrics. Dynamic graphs and heatmaps enable identification of common fault zones and high-risk regions, assisting maintenance planning. Filters based on time, fault category, or panel ID allow users to conduct focused analyses, while comparative views of pre- and post-maintenance images support repair evaluation. Together, the deployment and visualization components serve as a practical interface for both end-users and system administrators.

E. Grad-CAM Implementation

To improve model interpretability in our solar panel fault detection system, we integrated Gradient-weighted Class Activation Mapping (Grad-CAM). This technique generates heatmaps that highlight image regions most influential in the model's classification process. By computing gradients with respect to the last convolutional layer, Grad-CAM assigns importance scores to spatial regions and overlays the resulting activation map onto the input image. This visual explanation enables users to verify whether the model focuses on relevant fault areas, such as cracks or debris. Grad-CAM proves particularly valuable when integrated into the web application; whenever a fault is detected, the system provides not only a prediction but also a corresponding heatmap. This supports engineers in validating the decision, identifying misclassifications, and improving trust in AI outputs. Furthermore, Grad-CAM offers insights for model refinement by revealing instances where the attention diverges from the actual defect zones, guiding enhancements in both data and architecture.

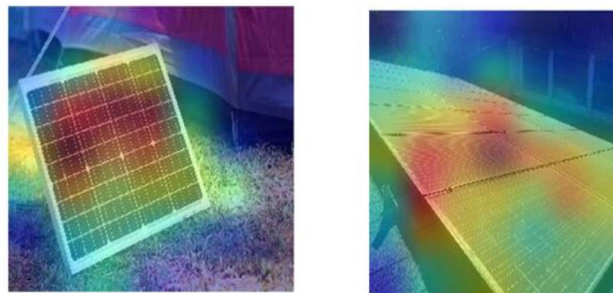


Figure 5: Grad-CAM images

Ultimately, the proposed pipeline transitions seamlessly from technical development to user-facing deployment, ensuring that model predictions are not only accurate but also interpretable and actionable. By integrating fault localization with severity assessment and maintenance recommendations, the system supports informed decision-making in solar panel management. This comprehensive approach demonstrates the potential of AI-driven diagnostics to optimize energy production, reduce operational downtime, and support sustainable infrastructure maintenance.

IV. RESULTS AND DISCUSSION

To ensure accessibility and usability, we designed a two-tier web application interface for solar panel fault diagnosis. The first version provides a minimal interface focused on image classification, while the second version introduces extended functionalities for deeper fault analysis.

The initial HTML web page offers a straightforward interface where users can upload an image of a solar panel for analysis. Once an image is submitted, the backend processes it using a pre-trained deep learning model and classifies it into one of six categories: dusty, snow-covered, bird drop, clean, electrical damage, or physical damage. Along with the predicted label, the system also provides a confidence score ranging from 0 to 1, which quantifies the model's certainty in its prediction. This confidence measure assists users in gauging the reliability of the outcome and making informed decisions regarding maintenance or inspection.

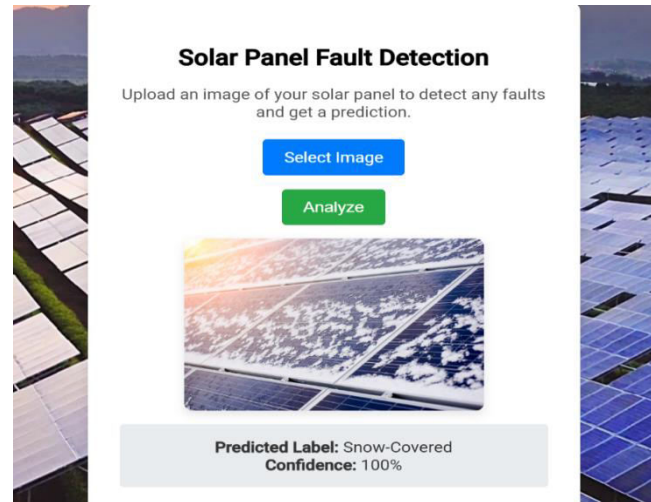


Figure 6: Web page 1

The extended version of the web interface enhances user interaction and delivers richer diagnostic insights. Users upload an image using the "Select Image" button and initiate processing by clicking "Analyze." The model returns not only the predicted fault label and confidence score but also additional metadata such as the severity of the fault, urgency of required intervention, and recommended corrective action. Furthermore, a Grad-CAM heatmap is displayed alongside the results, highlighting image regions that influenced the model's decision. These improvements create a comprehensive decision-support system for engineers and technicians in the field, supporting both rapid assessments and detailed evaluations. The interface demonstrates a successful prediction following an image upload. In the illustrated scenario, a snow-covered solar panel image is analyzed. The system accurately classifies the fault as Snow-Covered with 100% confidence. This strong confidence level suggests that the training dataset included sufficient examples of this fault class, allowing the model to generalize effectively. The HTML page confirms the prediction with a clean, user-friendly display of the label and confidence, reinforcing the model's trustworthiness. Such a setup is particularly beneficial for field use, allowing real-time diagnosis and rapid fault categorization. The visual interpretability through Grad-CAM adds transparency, enabling technicians to cross-verify fault regions, and minimizing reliance on black-box outputs. This overall integration of classification, visualization, and actionable insights elevates the interface from a basic diagnostic tool to a practical, field-ready AI system that aligns with real-world operational needs in solar panel maintenance.



Figure 7: Web page 2

This advanced HTML interface extends the diagnostic capabilities of the solar panel fault detection system. It provides not only basic classification but also actionable insights based on the uploaded image of a solar panel. The system returns detailed prediction results, including:

- Predicted Label: Dusty
- Confidence: 73.28%
- Severity: Medium
- Urgency: Within 3 days
- Recommended Action: Clean the panel to avoid loss
- Heatmap Visualization: Indicates image regions that influenced the model's prediction

The heatmap, based on model attention via Grad-CAM, highlights areas of concern in red and yellow, while cooler colors like blue denote regions of lesser importance. This interpretability layer enables users to quickly assess which portions of the panel require attention. This detailed feedback mechanism enhances the model's practical value, supporting informed decision-making in real-world maintenance scenarios. The system bridges AI predictions with field-level insights, helping prioritize faults by urgency and severity and guiding the necessary course of action.

Upon image upload, the system performs classification and returns a predicted fault label along with a confidence score. This helps identify common surface-level anomalies such as dust accumulation, snow coverage, cracks, or physical damage. In addition to classification, the system displays supplemental insights including severity level, urgency of required maintenance, and recommended corrective actions. A Grad-CAM heatmap is also generated to visually localize the fault, offering interpretability and confidence in the model's decision.

Figure 8 illustrates the confusion matrix for the solar panel fault classification model across six classes: dusty, snow-covered, bird drop, clean, electrical damage, and physical damage. The model correctly identified the majority of bird drop samples (35), showing high reliability for this class. Dusty panels were accurately predicted 26 times, with a few misclassifications primarily as bird drop. Snow-covered panels were correctly classified in 22 cases but confused with bird drop in 15 instances, likely due to similar visual textures. Clean panels had 17 correct predictions, with minor confusion involving dusty and snow-covered categories. Electrical damage was correctly identified 11 times, though some samples were misclassified as clean. Physical damage had 23 correct predictions with only minimal misclassification.

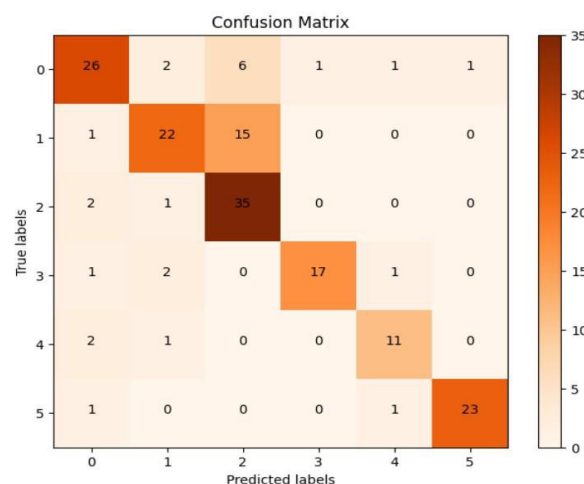


Figure 8: Confusion Matrix

Overall, the matrix demonstrates strong performance in identifying bird drop and physical damage, while snow-covered and dusty categories show moderate overlap.

V. 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., Alkaws, 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.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details