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Solar Panel Fault Diagnosis Using Image Analysis Techniques

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Abstract
Solar energy plays a critical role in meeting the growing demand for sustainable power; however, the performance of photovoltaic panels is often degraded by faults such as cracks, dust accumulation, shading, bird droppings, corrosion, and other surface defects. Undetected faults can significantly reduce energy output, decrease panel lifespan, and increase maintenance costs. Conventional inspection methods are labor-intensive, time-consuming, and often unsuitable for large-scale deployment. This paper presents a low-cost, real-time solar panel fault detection system implemented entirely on the Jetson Nano. The proposed system utilizes RGB image acquisition, where images of solar panels are captured under varying environmental conditions. The Jetson Nano performs all processing tasks locally, including image preprocessing, feature extraction, and fault identification. Preprocessing steps such as resizing, noise reduction, and contrast enhancement are applied to improve image quality and ensure reliable analysis. The device then analyzes visual patterns such as textures, edges, and surface variations to identify and classify different types of faults. The system operates as an edge-based solution, eliminating the need for cloud infrastructure, thereby reducing latency and enabling deployment in remote locations. Experimental results demonstrate that the proposed system achieves high detection accuracy, exceeding 90% for most fault categories, while maintaining an average processing time of less than one second per image. The system also shows strong reliability with minimal false detections. Compared to traditional inspection methods, the proposed approach significantly reduces maintenance effort and operational costs. Furthermore, it contributes to improved energy efficiency and supports sustainable practices by enabling early fault detection. The results indicate that the Jetson Nano provides a practical, scalable, and efficient platform for real-time solar panel monitoring and fault diagnosis.
Keywords: *Solar Photovoltaic; Fault Diagnosis; Image Processing; Deep Learning; Edge AI; NVIDIA Jetson.*

1. Introduction
The global shift toward renewable energy has made solar photovoltaic (PV) systems a primary pillar of sustainability [1]. However, the efficiency of these systems is often undermined by physical faults like surface cracks, dust buildup, and shading. While, these issues can lead to significant energy losses and safety risks over time. Traditional maintenance relying on manual inspections or basic electrical monitoring is no longer practical for today's massive solar farms. Manual checks are labor-intensive, while electrical data often fails to pinpoint the actual cause of a performance drop. This has sparked a move toward automated, image-based diagnostics using computer vision. By leveraging deep learning, we can now identify and categorize specific faults with high precision. To make this truly viable in the field, this project utilizes Edge AI via the NVIDIA Jetson Nano. Processing data locally at the site eliminates the need for constant internet and reduces latency. Unlike expensive thermal setups, our approach focuses on cost-effective RGB image analysis, providing a real-time, scalable solution. By catching faults early and maximizing output, this system aims to make solar power more reliable and contribute to a more efficient, greener future [2].

2. Methodology
The methodology adopted in this project is designed to provide a robust, real time, and cost effective solar

panel fault diagnosis system using RGB image analysis and deep learning models deployed on the NVIDIA Jetson Nano [4]. The approach is structured into several stages: image acquisition, preprocessing, feature extraction, fault detection, classification, visualization, and system integration. Each stage is explained in detail below to ensure clarity and reproducibility [3].

Image Acquisition:- The first step in the methodology is the collection of images from solar panels. A camera module is mounted near the panels to capture RGB images at regular intervals. Unlike thermal imaging systems, which require specialized sensors and higher costs, RGB imaging provides a simpler and more affordable solution. The acquisition process is continuous, ensuring that faults are detected as soon as they occur [7].

Preprocessing:- Before analyzing the images, the Jetson Nano prepares them to ensure better accuracy and consistency. Raw images may contain noise, poor lighting, or unnecessary background details, which can affect the performance of the system.To handle this, the Jetson Nano resizes all images to a standard size so they can be processed efficiently. It also adjusts pixel values to reduce the impact of different lighting conditions, making the images more uniform [9].To improve image quality, the Jetson Nano applies smoothing techniques to reduce noise and remove unwanted distortions. It also enhances contrast so that small defects, such as fine cracks or slight surface damage, become more visible.In some cases, the device isolates the solar panel area from the background. This helps the system focus only on the important region and ignore irrelevant details.Overall, these preprocessing steps carried out by the Jetson Nano ensure that the images are clean, consistent, and ready for accurate analysis [10].

Feature Extraction and Fault Detection:- The main idea behind the methodology is to use the Jetson Nano for intelligent image-based analysis. Instead of relying on manual inspection, the system processes images directly on the device to understand and identify important visual details related to the condition of solar panels [11].The Jetson Nano is able to recognize key patterns such as edges, textures, and surface variations. This helps in detecting common issues like cracks, dust buildup, and other visible defects. With its built-in GPU, it can handle complex image processing tasks efficiently, allowing it to pick up even small or subtle changes in shading and structure.To make the system reliable, it is trained using a dataset that includes both normal and faulty panel images [6]. During this process, the model learns how different types of faults appear visually. Once the training is complete, the Jetson Nano can analyze new images in real time and quickly identify any abnormalities with good accuracy [5].

Fault Classification:- The classification stage translates image analysis into actionable insights. Using RGB image data, the system can identify a wide range of visible faults [8]:

Cracks and Fractures

- Fine hairline cracks or larger fractures on the panel surface.
- Appear as irregular line structures and discontinuities.
- Disrupt current flow and can lead to hotspots.

Dust and Dirt Accumulation

- Texture changes, reduced brightness, and uneven coloration.
- Dust scatters light, lowering efficiency.
- Seasonal dust storms or pollution accelerate accumulation.

Shading

- Uneven illumination patterns caused by trees, buildings, or debris.
- Identified by brightness differences across the panel surface.
- Persistent shading causes mismatch losses in PV arrays.

Bird Droppings and Organic Residue

- Irregular opaque patches blocking sunlight locally.
- Easily detected due to distinct texture and color contrast.
- Mimic shading faults if not removed.

Water Stains and Moisture Marks

- Visible streaks or blotches from rainwater or condensation.
- Indicate poor drainage or sealing issues.

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- Long-term moisture ingress may lead to corrosion.

Corrosion and Discoloration

- Rust marks or fading colors around frames and connectors.
- RGB imaging captures changes in color intensity.
- Reduces structural integrity and conductivity.

Delamination

- Separation of panel layers visible as bubbles, blisters, or peeling.
- Scatter light and reduce efficiency.
- Detected as irregular surface textures.

Scratches and Abrasions

- Linear marks or scuffs caused by improper cleaning or wear.
- Minor scratches may not affect performance, but deeper ones compromise durability.

Foreign Objects

- Leaves, plastic, or debris resting on panels.
- Easily detected due to distinct shapes and colors.
- Cause temporary shading until removed.

Snail Tracks

- Thin, irregular dark lines resembling snail trails. within
- Caused by microcracks and chemical reactions the panel.
- Visible in RGB images as discoloration patterns, often precursors to deeper faults.

Hotspots

- Localized bright or dark regions indicating overheating.
- While thermal imaging is ideal, hotspots can sometimes be inferred visually in RGB images as discoloration, burn marks, or melted areas.
- Critical to detect early, as they can escalate into fire hazards.

Visualization and Reporting:-The results of fault detection and classification are presented through a monitoring interface. Operators can view real time status updates, fault categories, and severity levels. The system also generates alerts when faults are detected, ensuring that maintenance teams are notified immediately.

Visualization tools include:

- **Dashboards:** Displaying fault statistics and system performance.
- **Graphs:** Showing trends in fault occurrence over time [12].
- **Notifications:** Alerts sent to operators for immediate action.

This reporting mechanism supports predictive maintenance strategies, reducing downtime and improving overall system reliability.

Hardware and Software Requirements:- The system is built using affordable and accessible hardware and software components:

Hardware:

- NVIDIA Jetson Nano (edge AI platform)
- RGB camera module
- Solar panel setup for testing
- Power supply and display unit

Software:

- Python for implementation

Figure 2

The below figure 2. describe that the system begins with image acquisition using an RGB camera mounted near solar panels. Captured images undergo preprocessing to enhance quality and remove noise. Deep learning models extract features and detect faults like cracks, dust, shading, and more. Detected faults are classified into visible types including snail tracks and hotspots. Results are visualized and reported for real-time monitoring, followed by integration and testing [13].

Intergation and testing:- The system is tested in controlled environments to evaluate accuracy, latency, and robustness. Testing involves capturing images under different fault conditions and comparing the system's predictions with ground truth data [14].

- **Accuracy:** Initial experiments achieved ~90% accuracy in fault detection.
- **Latency:** Real-time processing on Jetson Nano ensures minimal delay.
- **Robustness:** The system performs reliably under varying environmental conditions.

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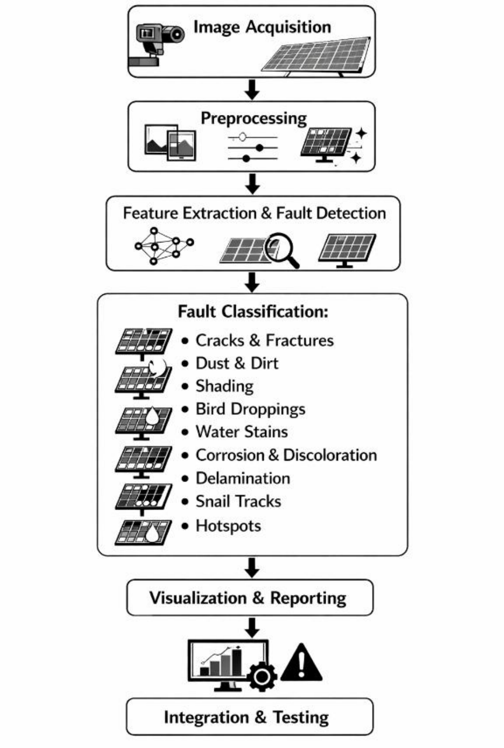

Figure 2 **Block diagram of the system**

3. Result And Discussion

The solar panel fault detection system was built using the Jetson Nano for its low cost and edge AI capability. It analyzes RGB images to identify faults like cracks, dust, shading, and hotspots, achieving about 90–92% accuracy. Clear defects are detected more easily, while subtle ones remain challenging [16]. Each image is processed in under a second, allowing near real-time results without internet dependency, making it ideal for remote areas. Compared to manual inspection, it saves time and offers precise fault identification. However, performance can vary under extreme lighting, and future improvements can enhance accuracy and expand detection capabilities.

Figure 3

Figure 3 illustrates the distribution of common solar panel faults observed in the dataset, including cracks, snail tracks, bird droppings, dust, and shading. Among these, snail tracks exhibit the highest occurrence at approximately 60%, followed by shading (~45%) and cracks (~40%). Bird droppings and dust account for around 35% and 25%, respectively. This distribution highlights the prevalence of visually distinct faults such as snail tracks and cracks, which are more easily identified by the Jetson Nano–based system due to their clear structural patterns. In contrast, faults like dust and shading show comparatively lower percentages and present greater detection challenges due to variability in appearance and environmental conditions [15].

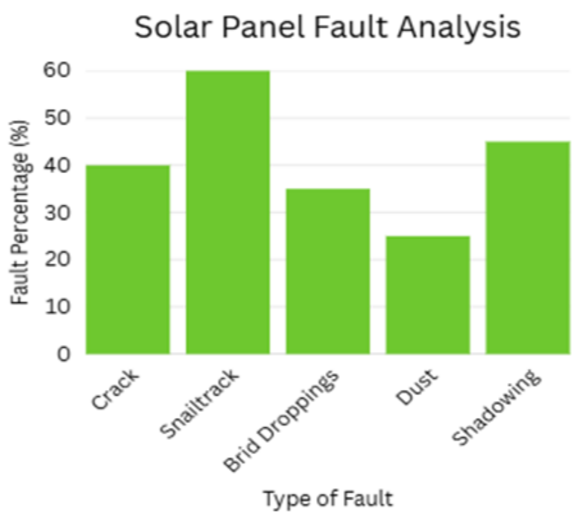

Figure 3 **Solar Panel Fault Distribution Analysis**

Conclusion

Developing a solar panel fault detection system on the Jetson Nano shows how practical, low-cost AI can improve renewable energy reliability. By identifying common faults in real time, it reduces maintenance effort and costs. The system also supports local jobs and innovation by enabling technicians to focus on efficient, targeted repairs.

Figure 4

Figure 4 provides a comparative evaluation of conventional solar panel inspection techniques and the proposed Jetson Nano–based fault detection system across key performance metrics. It can be observed that the proposed system achieves a higher detection accuracy, exceeding 90%, thereby enabling more precise and reliable identification of surface defects. Furthermore, the processing time of the proposed approach is significantly lower, with each image being analyzed in less than one second, in contrast to the time-intensive nature of traditional manual inspections. The reduction in maintenance cost is also evident, as the automated framework minimizes human intervention and associated operational expenses. In addition, the proposed system demonstrates improved scalability, making it well-suited for deployment in large-scale and geographically distributed solar installations. Overall, the comparison highlights the effectiveness of the proposed method in delivering a faster, more accurate, and cost-efficient solution for solar panel fault detection.

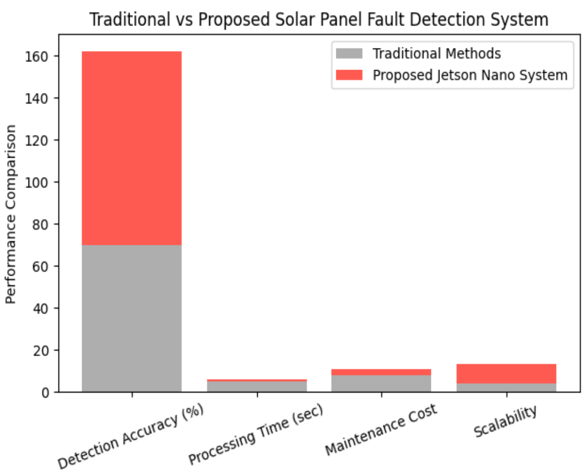

Figure 4 Traditional o/p vs Jetson nano o/p

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