Fault Identification of PV Cells in Solar Panel Using Reinforcement Learning

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Abstract: Electricity demand is increasing day by day and hence power utilities are slowly shifting towards renewable energy, mainly solar, as it is more reliable and environment friendly. However, solar power generation systems have very low efficiency and this is the major challenge faced by the researchers. Some of the reasons for the low efficiency is the presence of dust particles, bird droppings, shadows, rain droplets, microcracks etc. Out of these, microcracks can be avoided if detected on time whereas remaining parameters have to be addressed on a regular basis as they are issues related to environmental factors. Microcracks are mainly due to manufacturing defects as well as improper handling during transportation and installation. Manual inspection of panels to identify microcracks is both challenging and time-intensive, particularly for panels with large dimensions and high power ratings. This proposed work addresses the process of detection of microcracks using an improved technology which detects the crack within very less time as compared to the existing technologies. Reinforcement Learning method is used to detect and classify the solar panel images as either cracked or non-cracked.

1 INTRODUCTION

Solar panels play a critical role as a renewable energy source, offering a sustainable solution for reducing greenhouse gas emissions, lowering energy costs, and enhancing energy independence. They contribute to economic growth by creating jobs and have minimal operating costs. Renewable energy helps bridge the gap between electricity demand and generation, supporting a more balanced power grid. The cost of renewable energy technologies has dropped sharply in recent years, with the price of solar electricity falling by 85% between 2010 and 2020. As a result, renewable energy sources are becoming increasingly competitive on a global scale, particularly in developing countries, which are expected to drive the majority of future electricity demand. However, to ensure solar panels remain efficient and safe, early detection of cracks is essential for additional electricity. However, to maintain their efficiency and safety, detecting cracks in solar panels is crucial.

Cracks in solar panels can disrupt the flow of electricity, reduce energy output, and create safety hazards, such as overheating. Detecting cracks early helps prevent significant power losses, prolongs the lifespan of panels, and reduces repair costs. Techniques like electroluminescence imaging and thermography play a crucial role in quality control, performance monitoring, and ensuring the reliability of large-scale solar installations. Solar power generation has become one of the most favoured methods of electricity production in recent years. Out of the 173,619.21 MW of installed renewable energy capacity, solar power contributes 67,821.22 MW, accounting for 39.1% of the total. However, one major challenge in solar energy is its relatively low conversion efficiency. Factors such as dust accumulation, bird droppings, and microcracks negatively impact efficiency. Among these, dust, bird droppings, and shading should be addressed regularly throughout the panel's lifespan. Cracks are formed during the manufacturing process or transportation and installation. Therefore, it is essential to detect and repair them before the solar panel is commissioned. Due to the fine, hairline nature of cracks, highly efficient technology is required for their detection.

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2 LITERATURE REVIEW

Thermal image processing technique is used to identify cracks in solar panel. Infrared electromagnetic spectrum is analysed by capturing the thermal images of the solar panels using thermal camera. The variations in the captured electromagnetic spectrum are analysed to locate the cracked pixels. The authors obtained results of 95.1% sensitivity, 95.3% specificity, 95.9% accuracy and 95.1% precision using their proposed crack detection method(Singh , Kumar, et al. , 2018).

Vague rules based on Mamdani's argument for detecting cracked pixels in solar panel images. A pixel-based fuzzy rule is developed to classify each pixel in the solar panel image. The developed crack detection algorithm is tested on a set of 200 real time images to validate the proposed method's efficiency. (Chawla, Gupta, et al. , 2018). An electro photometric imaging technique for detecting or locating crack areas in solar instrument images. This solar panel image is transformed into frequency image using Discrete Fourier Transform (DFT). The two sides of the updated solar image are examined to determine the crack locations. The two sides of the updated solar image are examined to determine the crack locations. This method locates the cracked regions with its position coordinates and orientation. The results of 95.2% sensitivity, 95.9% specificity, 96.2% accuracy and 96.6% precision are obtained using the proposed crack detection method. (Dhimish, Holmes, et al. , 2019)

Transfer learning locates the defects both on centrally placed as well as decentralized solar panels. This CNN based model detects the defects with an accuracy of 98.9%. A multi-spectral deep CNN-based technique is a very good tool to locate visual defects with an accuracy of 94.3%. The effectiveness of the augmented data approach is carried out with the help of three distinct models. This method is very effective than the typical data augmentation approach. (Ding, Zhang, et al. , 2018). Brand-new unsupervised technique for figuring out the mapping that turns crack images into binary images. Using a Generative Adversarial Network (GAN), they achieved this. To improve fracture localization precision, the investigators updated the architecture by introducing a cyclic consistent loss. While the generator part of the GAN uses eight residual blocks connected in a convolutional neural network (CNN) to obtain features, the discriminator uses a 5-layer fully convolutional network. A full analysis of the suggested paradigm is done, along with comparisons of qualitative and quantitative data. The results of the investigation show that the suggested strategy outperforms many other popular strategies for crack picture interpretation. (Duan, Wang, et al. , 2020)

Deep convolutional neural network (CNN) for the detection of robust damage with very good accuracy. They have collected high-definition images of hydro junction infrastructure using a camera and pre-processed the same using image expansion technique. This image is trained and tested using Inception-v3 deep learning method for the detection of damage. The accuracy of the method is 96.8% which is more than the accuracy from the method using Support Vector Machine (SVM). [(Feng, Liu, et al. , 2019) crack detection by using an automated framework with combination of stereo vision and deep learning technique. They have developed a comprehensive dataset of colour images of a road along with its depth and colour depth overlapping. To reduce the computational complexity a modified U-net deep learning architecture is developed. It incorporates depth wise separable convolution method. This method gives accurate measurement of the volume with the help of high resolution segmentation map. (Guan, Li, et al. , 2021). An enhanced method for fusing (EL) images and it entails five critical stages and fewer seconds. The use of low-sensitivity Charge Coupled Device (CCD) cameras is insufficient for accurate fracture identification and localization using EL imaging. Large amount of time and energy have been put into perfecting and enhancing this method. The authors have carried out an analysis on the time taken for detecting the faults on large set of EL images in this work. (Haase, Müller, et al. , 2018). A new method for finding cracks in faults with dark colours and poor contrast by combining rapid discrete curvelet waveform and surface evaluation. The original image is divided into its component parts and then recreated using the FDCT (Fast Discrete Curvelet Transform) technique. In order to remove surface textures from the images, constraints for the decomposition parameters are derived using texture feature measurements. Contours from the rebuilt images are obtained, which are fracture fault contours, to produce the required image. (Li, Zhang, et al. , 2014)

A machine vision-based system for the automation of crack detection. Image acquisition and processing for separation size estimation are performed using a single camera. They have developed a crack detection algorithm using HSB and RSV crack models, where cracks are identified based on image sequencing. Images are given as the input to the proposed algorithm and a new image with cracks highlighted using red particles is generated.

The crack measurement algorithm takes input from a vector in which pixel coordinates of the detected crack are stored. The algorithm calculates the crack amplitude by counting the number of pixels in the cross section. (Lins, Silva, et al. , 2016). An altered segmentation algorithm in combination with the ORing approach to further decrease the detection and calibration time. The EL imaging may take up to 5 seconds, however processing the calibrated pictures takes around only 0.1-0.3 seconds(Mather, Thompson, et al. , 2020).

3 PROBLEM STATEMENT AND EXISTING SYSTEM

In solar panels, energy production is influenced by the efficiency of the photovoltaic (PV) cells and maintaining clean, dust-free panels. Defects in PV cells significantly affect the overall energy output, leading to reduced efficiency and, consequently, financial losses. Several methods, including LabVIEW-based techniques, IoT-enabled systems, Wi-Fi modem control, and YOLO V5 technology, are currently employed to detect cracks in PV cells. However, each of these methods comes with its own limitations. These include the need for extensive datasets, potential cybersecurity risks, lack of transparency (due to black-box algorithms), and challenges in distinguishing between different textures. Additionally, time is wasted on tasks like monitoring rollers and clearing debris, such as nails, during operation. This not only reduces efficiency but also increases the risk of accidents, sometimes causing severe injuries like finger damage or even fractures to workers.

4 BLOCK DIAGRAM

In the proposed approach, cracked and non-cracked solar panels are categorized using a Continuous Wavelet Transform (CWT)-based RIL classification method. A Gaussian filter is applied to the solar panel images to detect and eliminate blurring along the edges of cracked pixels. The pre-processed images are then decomposed into sub-band images using CWT. Texture and statistical features are extracted from these decomposed sub-bands and classified by the RIL classifier, which determines whether the solar panel image is cracked or intact. A segmentation algorithm is applied to the classified cracked images to pinpoint the cracked pixels. Since RIL is an autonomous learning-based system, crack detection is simplified, eliminating the need for extensive datasets. Figure 1 illustrates the block diagram for fault detection in photovoltaic cells using the RIL method.

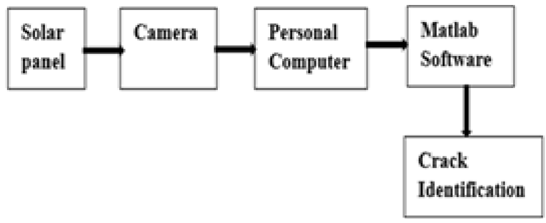


Figure 1: Block Diagram of fault identification of PV cells in solar panel using RIL.

5 HARDWARE DESCRIPTION

5.1 Camera Module

A 720-pixel camera, also known as a 720p camera, records video at a resolution of 1280 x 720 pixels. This falls under the High Definition (HD) category, providing a reasonable level of image clarity. The camera captures visuals with 1280 horizontal pixels and 720 vertical pixels, resulting in a resolution of roughly 0.92 megapixels, which is sufficient to deliver HD-quality images. One advantage of 720p cameras is that they require less bandwidth for streaming and consume less storage space for recordings compared to higher resolutions, making them ideal for continuous recording, cloud storage, or streaming on lower-speed internet connections. The camera is typically mounted on a stand and used to detect the presence of cracks or defects in the photovoltaic cells of solar panels.

5.2 Solar Panel

Solar panels consists of photovoltaic (PV) cells that convert sunlight into electricity. They form a crucial part of solar energy systems, operating on the principle of the photovoltaic effect. The solar panel used in this proposed work is made from either monocrystalline or polycrystalline silicon. Typically, solar panels have a lifespan of 20 to 30 years, though their durability is largely influenced by environmental factors. Physical damage, such as cracks in the PV cells, can significantly impact their performance and efficiency. Detecting cracks in solar panels is critical for maintaining optimal energy production, preventing further deterioration, and ensuring the safety and longevity of the system. The solar panel used here generates an output of approximately 9 volts.

6 SOLAR CRACK IMAGE PROCESSING

The proposed schemes for cracked and non-cracked solar panel classifications are depicted in Figure 2.

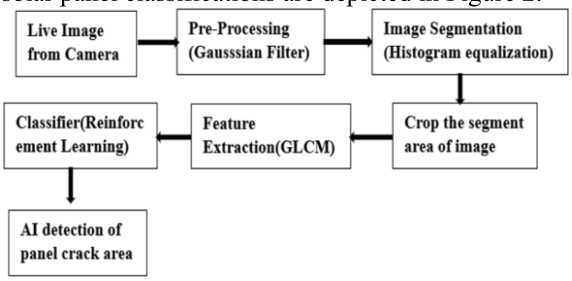


Figure 2: Block diagram of work flow of crack detection

In this proposed work, the cracked and non-cracked solar panels are classified using CWT-based RIL classification method. A Gaussian filter is applied to the solar panel image to detect and remove blurring at split pixel edges. The pre-processed image is now decomposed into sub-band images using CWT. The texture and statistical features are computed from the decomposed sub-band images, and these features are classified using the RIL classifier, which classifies the solar panel image into either cracked or non-cracked image. The segmentation algorithm is now applied on the classified CSP image to detect the cracked pixels. The task of detecting cracks in solar panels begins with a high-resolution camera taking live images of the panel. This raw image data is then subjected to preprocessing, where a Gaussian filter is applied. After preprocessing, the image is segmented using histogram equalization. This technique improves image contrast, making it easier to distinguish between areas, such as cracks and cracks.

The classification system also divides the image into smaller, more manageable parts, and draws attention to areas likely to crack. Once the classification is done, segmented areas of interest are cropped from the image to focus the analysis mainly on these regions, reducing the complexity of the dataset. Then, feature extraction is performed on cropped segments using the Gray Level Co-occurrence Matrix (GLCM). GLCM is a statistical technique that analyzes texture by examining the spatial relationships between pixels in an image. This helps to capture important information about the surface morphology of the solar cell, which is essential for accurate crack detection. The extracted features are then fed to the classifier, which uses reinforcement learning (RIL) techniques.

The RIL classifier is trained to recognize the shapes of the extracted features and classify the image as fragmentation or non-fragmentation. Reinforcement learning continues to improve its accuracy by learning from feedback, making it a robust method for classifying such images. Finally, based on the output of the classifier, the exact locations of cracks in the solar array are identified. The AI system highlights these damaged areas, allowing for more accurate detection of faults in the track.

6.1 Separation Classification Algorithm

The crack segmentation algorithm is a crucial step for identifying and isolating crack regions in a fractal solar panel image. The following steps outline the detailed process for effectively classifying fractal regions in a solar device image:

Step 1: Suppression of boundary-related outlier pixels: Start by eliminating outlier pixel structures linked to the boundaries in the classified fractal solar panel image. This helps remove unnecessary pixels along the edges, which are often noisy and not part of the actual crack.

Step 2- Pixel insertion: This step focuses on low-energy extraction regions, typically representing crack areas in the solar cell, to ensure that only significant crack regions are retained for further analysis.

Step 3-Expansion using a disk structural element: Apply an expansion operation using a 'disk' structural element with a radius of 13 mm to enlarge the image. This expansion process helps expose fracture zones, increasing visibility and overlap, which is useful for identifying larger crack structures.

Step 4-Iterative enhancement: The expanded image undergoes the same enlargement process in repeated iterations. This further emphasizes important areas, allowing smaller cracks or minor differences to merge into larger visible sections, clarifying the crack structure.

Step 5-Erosion using a disk structural element: Use an erosion operator with a 'disk' structural element of 5 mm radius to erode the enlarged image. The purpose of this erosion is to thin out the thickened edges from the expansion phase and restore the crack to its original width while maintaining continuity.

Step 6-Application of the thin operator for final segmentation: Finally, apply a 'thin' operator to refine the segmented image by removing any unnecessary pixels, ensuring no gaps. This operator enhances the segmented image by breaking down larger sections and providing a more accurate representation of the final crack structure.

6.2 Prototype Model

The prototype shown in Figure 3 represents a solar panel separation system that integrates machine learning technique to ensure accurate and reliable detection of defects in Photovoltaic (PV) panels. The installation includes a camera with high resolution mounted on metal stands to capture images of the sun in real time panel below. Here it is used two panels for identifying the cracks with one defective and the other with non-defective.

These images are processed on a laptop connected to the system, where sophisticated image editing is performed. Initially, the images are subjected to Gaussian filtering, an important preprocessing step to remove noise and increase the clarity of pixel boundaries, especially in areas of potential fragmentation followed by histogram equalization contrast is effective and ensures that the distinction between cracked and uncracked areas is clear. After preprocessing the image, the Gray-Level Co-Occurrence Matrix (GLCM) is used for feature extraction. These features are encountered in a reinforcement learning (RIL) classifier, which is trained to distinguish between images of damaged and undamaged panels. The classifier produces a binary result, indicating if there is a crack in the screen. It uses thresholding to remove redundant pixel data, width erosion operators to correct segmented crack edges.

Figure 3: Prototype Model.

7 RESULTS AND DISCUSSION

In this proposed work, the cracked and non-cracked solar panels are classified using RIL classification method. A Gaussian filter is applied to the solar panel image to detect and remove blurring at split pixel edges. The pre-processed image is now decomposed into sub-band images. The texture and statistical features are computed from the decomposed sub-band images, and these features are classified using the RIL classifier, which classifies the solar panel image into either cracked or non-cracked image. The segmentation algorithm is now applied on the classified image to detect the cracked pixels. The proposed schemes for cracked and non-cracked solar panel classifications are depicted in the following figures.

The task of detecting cracks in solar panels begins with a high-resolution camera taking live images of the panel. This raw image data is then subjected to preprocessing, where a Gaussian filter is applied. The Gaussian filter smooths the image by reducing noise and blurring, especially around pixel edges that may correspond to cracks, and ensures that the image is clearer and more suitable for subsequent analysis. After preprocessing, the image is segmented using histogram equalization. This technique improves image contrast, making it easier to distinguish between areas, such as cracks and cracks. The classification system also divides the image into smaller, more manageable parts, and draws attention to areas likely to crack. Once the classification is done, segmented areas of interest are cropped from the image to focus the analysis mainly on these regions, reducing the complexity of the dataset. Then, feature extraction is performed on cropped segments using the Gray Level Co-occurrence Matrix (GLCM). GLCM is a statistical technique that analyses texture by examining the spatial relationships between pixels in an image. This helps to capture important information about the surface morphology of the solar cell, which is essential for accurate crack detection. These textual features such as contrast, correlation, intensity, and equivalence provide valuable information for classification.

The extracted features are then fed to the classifier, which uses reinforcement learning (RIL) techniques. The RIL classifier is trained to recognize the shapes of the extracted features and classify the image as fragmentation or non-fragmentation. Reinforcement learning continues to improve its accuracy by learning from feedback, making it for classifying such images. Finally, based on the output of the classifier, the exact locations of cracks in the solar array are identified. The AI system highlights these damaged areas, allowing for more accurate detection of faults in the track.

The results as shown in Figure 4 and Figure 5, demonstrate the effectiveness of the implemented crack classification scheme in structural damage detection in solar panels. In Figure 5 refers to a physical solar panel with visible cracks extending across its surface. It serves as the raw visual data used. Although cracks are lightly visible to the naked eye, detecting and measuring them requires sophisticated operational techniques to ensure accurate detection under lighting conditions and other possible noises. With various steps a preprocessing was used to enhance the image interpolation, from Gaussian filtering It helps to make it clear that they can prevent crack detection accurately. When the image suffers from poor lighting or when the separation is weak increased contrast made the separation more distinct. Figure 5 shows the results of the classification process, where cracks appear as distinct black areas on a white background, representing intact parts of the panel. Advanced extraction techniques are used, with grey level co-occurrence matrix (GLCM) performs the classification detects texture differences between cracked and uncracked regions.

Figure 4: Sample Panel 1

Figure 5: Cracked area

When the new, undamaged solar panel shown in Figure 6, is placed under the system for analysis, the resulting image classification system confirms that there is no cracking or structural damage as shown in this Figure 7, the classification system does not show any error areas, and produces a consistent separation of output pixel values without dark areas that means the fracture is still the same, nothing wrong is detected, and it is secure if the panel is true. The reinforcement learning (RIL) classifier used in the system reveals the intact state of the solar panel by classifying the panel as non-defective with a binary output of '0' This result indicates that system is better able to distinguish between damaged and undamaged panels.

Figure 6: Solar Panel 2

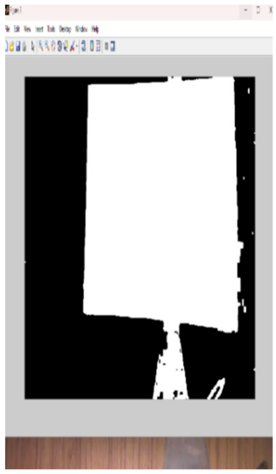


Figure 7: Uncracked area

The graph in Figure 8 illustrates a comparison of classification accuracy of crack identified panel and the reinforcement learning (RIL) classifier across various dataset sizes. The x-axis indicates the size of the dataset utilized for training and testing, while the y-axis reflects the accuracy of each classifier.

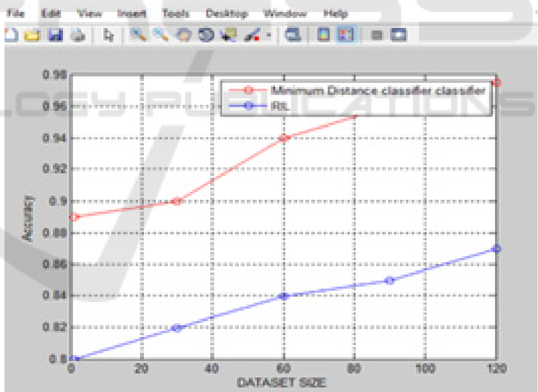


Figure 8: Graphical representation of accuracy.

Gray layer co-occurrence matrix (GLCM) table 2 is needed to detect cracks in solar panels by quantifying texture features after image preprocessing and segmentation It examines pixel interactions at angles (0°, 45°, 90°, and 135°) to detect subtle anomalies. Key features include contrast (strong contrast for separation), correlation (pixel shape reflecting structural information), robustness (uniform and dense textures), homogeneity (near diagonal for texture accuracy) and entropy (complex destructive text).

Table 1: Results of sample solar panel.

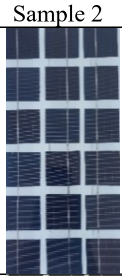
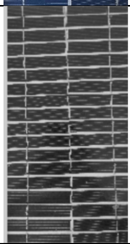
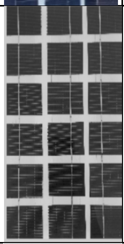
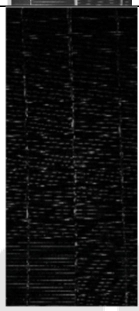
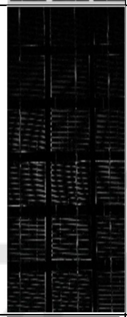
Steps	Sample 1	Sample 2	Output
Sample solar panel			Original Solar Panel for analysis
GLCM Feature extraction			Grayscale texture analysis of panel
Normalize wavelet			Normalize Wavelet image for better resolution
Crack identified area			Cracks identified areas
Crack segmented part			Crack segmented regions
Resolution	300 x 168	275 x 183	
Status of sample image	Cracks identified	Cracks not identified	Status observed

Table-1 represents the sample solar panel was performed using Reinforcement Leaning technique to identify the cracks. Two samples are evaluated from their original image for further process. Wavelet transformation was then applied to normalize the image resolution. In sample-1, cracks were identified and segmented by confirming damage with a resolution of 300x168 pixels. In sample 2 shown no evidence of cracks with its resolution recorded as 275x183 pixels.

Table 2: Properties of GLCM.

Features	Cracked Panel	Non Cracked Panel
Contrast	0.45	0.12
Correlation	0.28	0.75
Energy	0.12	0.72
Homogenity	0.35	0.85

8 CONCLUSION

In conclusion, the application of Reinforcement Learning (RIL) for fault identification in Photovoltaic (PV) cells offers numerous substantial advantages. This cutting-edge approach showcases the potential of advanced machine learning techniques to enhance the efficiency and reliability of solar energy systems. Through reinforcement learning, the model continuously learns and refines its ability to detect cracks in solar panels, leading to significant improvements in both maintenance and overall system performance. The combination of image processing with RL algorithms enables precise crack detection, reducing the costs linked to manual inspections and preventing energy losses. Additionally, the adaptive learning nature of the RL-based model allows it to evolve over time, handling various types of cracks and improving its robustness in diverse environments. This adaptability provides a level of flexibility and convenience that is especially valuable in modern industrial applications.

Looking ahead, integrating a smart device used to identify the cracks on the top layer of solar panels offers future potential, where operators can remotely control and manage the process through a user-friendly interface available via web or mobile applications. This remote monitoring capability enhances operational efficiency proposed work underscores the transformative potential of AI-powered approaches in optimizing and maintaining solar panels, offering a scalable, automated solution that enhances the durability of PV cells. Future work could focus on expanding the dataset, optimizing the algorithm for real-time processing, and incorporating predictive maintenance features. This solution marks a promising advancement toward making solar energy systems more efficient, cost-effective, and sustainable.

9 FUTURE SCOPE

Looking ahead, there is significant potential for further advancements and innovation in this field. The current system could benefit from incorporating larger datasets, which would enhance the performance of the RIL classification method and potentially increase its accuracy. Another area for improvement is the development of multiclass fault detection algorithms capable of identifying other types of faults beyond cracks, such as hot spots, debris, and microcracks, all of which can affect the performance of solar panels. This would enable remote monitoring and quicker fault detection.

Furthermore the solar crack detection system can be made as a portable system for detecting the cracks in large solar farms and in remote areas enhancing panel efficiency and life span. This portable crack detection tool can be used by on-site engineers to inspect smaller solar setups. Also cracks in solar panels installed in large areas can be detected by using a drone to capture the images of panels and then to undergo the crack identification procedure. Additionally, integration with AI and IoT will improve detection accuracy and enable automated alerts. This innovation supports sustainable energy by minimizing waste and ensuring optimal solar panel performance.

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