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Dust Detection and Cleaning Optimization in Solar Power Systems Using Computer Vision and Machine Learning for Improved Efficiency

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ABSTRACT

Solar energy is the key in addressing the energy problem in the world because it produces clean and renewable energy. Nevertheless, environmental conditions, especially dust collection that decreases the intensity of lights on the surface of the panel and consequently, influences the energy production, significantly influence photovoltaic (PV) panel efficiency. This paper proposes using artificial intelligence (AI), computer vision, and a smart dust-detecting system that can detect the status of a solar panel in real-time, which will help the research to go beyond this hitch. To obtain the real-time images of the glass of a similar dimension to a 200 x 200 mm solar panel, the proposed system includes a Raspberry Pi and a camera module. Convolutional Neural Network (CNN) is utilized to analyse such images and classify with an accuracy of 94.53% to signal preventive maintenance alerts on areas where dust is detected. Also, a second model involves the implementation of Gray Level Co-occurrence Matrix (GLCM) features and Local Binary Pattern (LBP) features combined with Support Vector Machine (SVM) classification having accuracy of 94.3% in recognition of moderate to heavy dust loads using visible light pictures. The findings demonstrate that AI-based predictive maintenance will play a significant role in maximizing efficiency as solar panels can be monitored automatically, cost-efficiently, and at a large scale scales with or without human labor intervening, particularly in remote locations and distributed locations. Although the results confirm the operational advantages of smart detection of dust, the research shows that additional empirical findings are required to modify and generalize such solutions within various conditions of the environment

Introduction:

The move to use sustainable energy on a global scale has shone the light on solar photovoltaic (PV) system as one of the renewable energy responses because they provide clean, decentralized, and economical electricity[1-3]. Solar energy is an alternative to conventional fossil fuel that can be used because it is plentiful and it does not harm the environment[1-4]. Nonetheless, PV systems in the context of efficiency and longer-range performance is influenced highly by environmental phenomena, more specifically, the level of dust deposits on the surface of panels[4-5]. Soiling minimizes the transmission of sunlight, decreases the process of photoelectric conversion resulting into energy losses in excess of 30 percent in dry and dusty areas[28-30]. Manual inspection and cleaning techniques are ineffective, time-consuming, and inconsistent and so cannot be used in large scale or remote installations. To deal with these problems, computer vision, machine learning, and embedded IoT platforms, are being used to create intelligent and automated monitoring that has become revolutionary solutions. This paper suggests a low cost application of dust detection system based on Raspberry Pi platform with camera module and a Convolutional Neural Network (CNN), which can determine the soiling status with more than 94 percent accuracy [11]. A hybrid support vector machine (SVM) feature-based model which includes local binary pattern (LBP) and the gray level overlap matrix (GLCM) enhances dust classification levels[6]. With proactive, remote, and real-time regular consumption made possible by powered by AI techniques, time is reduced, and reliability is improved. Weather-adaptive controls, applications for smartphones, and SCADA systems can all be used to centrally, effectively, and responsively work rooftop solar panels. The system's performance is further improved by more advanced methods including remote servicing in AR/VR, self-diagnosing systems, and predictive maintenance. Generally speaking, a smart monitoring system like this not only addresses one of the most serious problems—excessive dust deposits—but it also advances the creation of self-sufficient and sustainable solar power systems[3].

Literature Review:

As priority turns toward more sustainable options According to studies, photovoltaic, or solar PV, systems are essential for meeting the world's energy needs as they are distributed, clean, and cost-effectiIn dust surroundings, In dust surroundings, soiling—the accumulation of dust on panels—remains a significant bottleneck, reducing energy efficiency and irradiation by about 30% [4–5,26,28–30] and Deepak and Malvi [5], explored how dust type and environmental factors influence performance loss, while others [26–28] emphasized site-specific variability. Although being commonly employed, conventional human cleaning methods were inadequate expensive, and time-consuming. As the result, researchers like a Sarver et al. [29] and Abuqaauud and Ferrah [22] reviewed by automated technologies including hydrophobic coatings and robotic wipers. Consequently, The researchers such as Sarver and colleagues [29] and Abuqaauud and Ferrah [22] was examined automated technologies, such as robotic wipers and hydrophobic coatings. However, the remedies are ineffective until soiling takes place. Due to this constraint, very quick identification through the use of artificial intelligence (AI) and computer vision has gained attention. For The satellite imagery, so and Tsatsoulis [7] and Clausi [8] improved by the Gray Level Co-occurrences Matrix (GLCM), which was has the first presented by Haralick et al. [6] and analyzes spatial pixels relationships. Materka and Strzelecki [10] identified the important textural parameters (contrast, entropy, homogeneity) for the dust detection. In the parallel or Local Binary Patterns (LBP) by Ojala et al. [9] captured the local texture features efficiently, and combining LBP with GLCM features improved the classification accuracy by the uniting local and global textural information. Support Vector Machines (SVM) that the formalized by the Cortes and Vapnik [13] and which further the explained by the Hsu et al. [14], became the popular classifiers for these features, offering strengthg against the high-dimensional data and the reliable categorization of dusty versus clean panels under varying conditions. CNNs were first developed by LeCun et al. [11] and Krizhevsky et al. [12], but the development of deep learning, a technique which continually acquires hierarchical spatial properties and achieves excellent accuracy in identification, as shown by Aji et al. [21], has drastically changed CNN programs. CNNs improved that the real-time dust detection in addition to handcrafted features which is scalable remote oversight was made possible by IoT frameworks and its developed by Zanella et al. [16] and Gubbi et al. [17], edge computing which solutions developed by Yu et al. [18], Miorandi et al. [19], and Borgia [20] decreased latency by processing the data closer to the sensors. complimentary strategies, such as the integrating SCADA [24],UAV-based inspections [25], and predictive maintenance frameworks [23], further the support the operational efficiency of the Collectively, the literature it shows a clear evolution: from manual and reactive methods to intelligent the proactive systems combining AI, texture analysis, SVMs, deep learning, IoT, and edge of computing and making PV energy production more reliable, cost-effective, and it sustainable even under challenging environmental conditions.

2. **The background Information in The science of mathematics**

2.1 GLCM, or the Gray Level Co-occurrence Matrix: In image processing and computer vision, the Gray Level Co-occurrence Matrix (GLCM) is a potent statistical technique that examines the spatial relationship between pixel pairs to extract second-order textural information from grayscale images. first appeared in 1973 by Haralick et al[6]. In areas including the materials science, industry inspection, satellite imagery, or imaging in medicine GLCM is now commonly used [7-8].

It determines the rate of occurrence of a single pixel with brightness (i) at a specific gray-level to a separate picture with intensity (j) at a given distance (d) and angle (θ). The often used ratios of 0° (horizontal), 45° (diagonal), 90° (vertical), and 135° (anti-diagonal) offer an extensive way of expressing the texture of images according to pixel separation and spatial orientation. P(i,àj; d,¸), also known as the Gray Level The co-occurrence Matrix (GLCM), lists the probability of two pixel of gray level i and j at a given distance d and direction θ in an image denoted as $P(i, j; d, \theta)$, is defined as the number of times two pixels with gray levels i and j occur at a specific distance d and orientation θ within an imageThe empirical illustration illustrates the spatial relationship among pixel pairs by using θ to indicate the direction and θ to indicate the distance between the pixels. So θ is 90° (vertical), 45° (diagonal), 0° (horizontal), and 135° (anti-diagonal) data.

The GLCM gives important information on the texture and structure of the image by calculating these a combination frequency all through the entire image at different offsets and angles[6-7].

2.2 Textural Qualities With GLCM

After the building of the gray level co-occurrence matrix (GLCM), an array of statistical properties, like consistency, contrary, granularity, and softness, can be retrieved to describe a picture's texture[6-8]. The normalized matrix values p(i,j)p(i, j)p(i,j), which indicate the proportional number of gray-level co-occurrences at particular places and the underlying cause of these features. Important descriptors Which include Contrast that measures the intensity difference between adjacent pixels and is higher for images with more spatial variation, and Energy (Angular Second Present), which measures texture uniformity and is higher for simpler textures. Similarity (Inverse Difference Moment), which measures how closely the arrangement of elements is to the matrix diagonal which shows smoother textures if high and connection between demonstrates the linear dependence of gray levels and is derived by using the means and standard deviations of the marginal probabilities. Entropy uses the small variable ε\varepsilonε to prevent the logarithmic mistakes and assesses the degree of disorder or intricacy in this texture[6,7], with the greater values for suggesting more irregular patterns. While autocorrelation watch the product of grey-level pairs weighted by their likelihood, dissimilarity measures the total disparity between neighbouring pixels gray levels. Asymmetry in the pattern of pixel strength co-occurrences is finally shown by the Cluster Shade, which assesses the surface distributions skewness and When combined, these features offer an in-depth understanding of the textural for profile of a picture[10].

Support Vector Machine

The long-term which reliability of the support vector machine (SVM) and especially in binary sorting scenarios that renders it an increasingly common supervised machine learning method. It operates the determining which hyperplane best divides data points from the two classes and in this instance, dust-accumulated and clean solar cells. Paired with suitable kernel and functions such as polynomial, linear, radial basis function (RBF), o sigmoid kernels, SVM performs well in the high-dimensional feature spaces and it is especially skilled at the managing non-linear interactions. The model which works similarly to a two-layer feedforward neural network when a sigmoid kernel is used but it frequently exceeds neural networks in terms of computational efficiency, ability to prevent overfitting, particularly when the working with highly dimensional and complex datasets.

2.3.1 Pattern of Local Binary (LBP)

A strong feature which descriptor for the describing local textures in grayscale photos is LBP. By thresholding the vicinity of the each pixel and calculating the histogram of these patterns, it gives each pixel a binary code. Particularly helpful for the capturing edge, corner, and flat area characteristics that aid in distinguishing dusty from clean surfaces are the uniform LBP patterns, which are the maximum of two bitwise transitions (e.g., $0 \rightarrow 1$ or $1 \rightarrow 0$).

2.3.2 A method for detecting dust **:** Three stages make up the dust detection method, as shown in Figure : Getting clean, dust-free pictures of solar panels was part of the photo acquisition and preparation procedure. ·Feature description: a feature descriptor for each distinct solar panel image is created by the combining the histogram of LBP uniform patterns and GLCM textural features which Training a linear support vector machine classifier the feature descriptors of images of solar panels in both dust-accumulated and the clean states is the first step in creating a classification model.

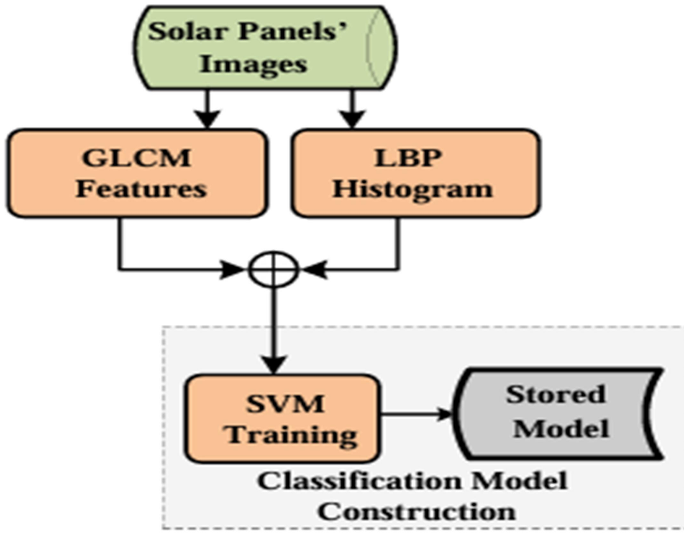


Diagram for the dust detection figure[1]

DATA Durability

The efficacy and accuracy of any machine learning-based classification of images system is greatly affected by the calibre and accuracy of the dataset used. The proposed dust detection look at there was developed and verified by the employing a large dataset of the solar panel photographs obtained in the different climatic conditions.

Creating Up Images Collection

An RGB camera with a 20 megapixel resolution was utilized for taking images of a solar panel so as to ensure the excellent surface detail required for subsequent feature mining. The image acquisition process was carried out by hands between 10:00 AM and 4:00 PM, when there is a significant variation in the strength of natural light. This schedule was decided by the simulate a wide range of visible illumination conditions which including both sunny and overcast days, in the order to mimic the actual operating conditions of the solar panels in the outdoor settings. These pictures which is depict on the patterns of dust accumulation based on by the exposure to the environment were taken outside to accurately mimic real installation scenarios. Nevertheless, by physically covering the solar panel's surfaces with varying quantities of sand and dust To enhance the dataset by adding controlled variability, the artificial dust accumulation was generated. Moderate and severe dust accumulation were the two categories into which the dust levels were separated.

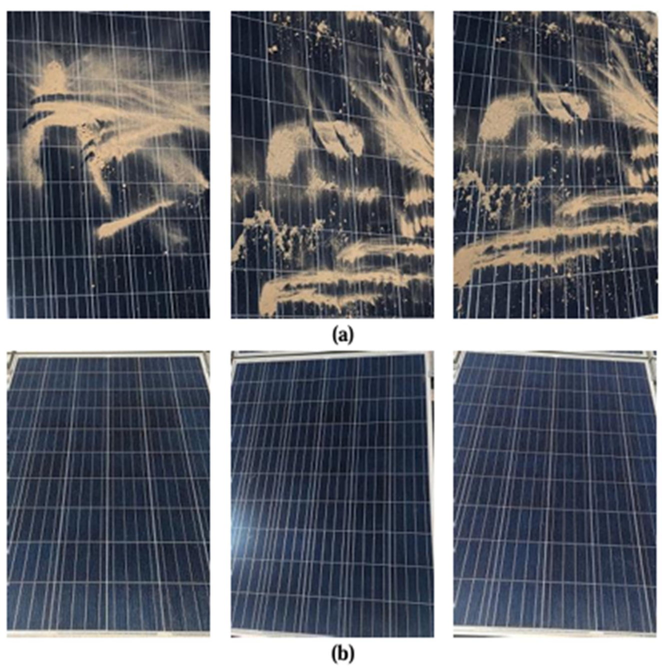
Methods of Image Acquisition

The digital camera was fixed on a selfie stick and that could be the adjusted from 1.5 to 4 meters in height to simulate the potential and height of a robotic inspection arm used in automated dust detection systems. This arrangement made it possible to take the pictures from different heights and perspectives which is increased the datasets clearity and realism.

Pre-processing Images

• Resizing: By the lower computational complexity while maintaining the pertinent visual details and images were downsized to the standard resolution of these 650 × 875 pixels.

• Cropping: To separate and emphasize the solar panel area in each picture, background noise and extraneous surrounds were removed by the using manual cropping.



(a)

(b)

Sample images of solar panels with: (a) Accumulated dust and (b) Clean condition figure[1]

Conclusion:

These techniques for the percentage points of the arms that are frequently seen in the automated systems using the images captured with a manually operated by camera setup in the natural sunlight. Panel conditions were categorized of using a Linear Support Vector Machine (SVM), which is trained by the features collected using two widely used these texture descriptors that is Local Binary Patterns (LBP) and Gray Level Co-occurrence Matrix (GLCM). A total of the four experimental models were which constructed utilizing from different combinations of the descriptor features which is Based on the findings by the four algorithms showed excellent classification of accuracy and performance rates of 86.8%, 92.5%, 94.3%, and 86.8%, respectively. The method mimics of the viewpoint of robotic arms typically found in automated systems by using the photos obtained with a manually operated camera setup under the real-world lighting conditions. Panel conditions were categorized by the using a Support Vector Machine (SVM) trained on this feature extracted using two widely used the texture descriptors: Local Binary Patterns (LBP) and Gray Level Co-occurrence Matrix (GLCM). Total four model experiments were built by using the various feature descriptor pairings by The results showed that the four models had good classification performance, with accuracy rates of 86.8%, 92.5%, 94.3%, and 86.8%, respectively. These findings confirm the robustness of the proposed feature and extraction method which is demonstrate to that SVM is a suitable and very effective classifier for this dusting problem. The suggested approach shows tremendous potential as the reliable alternative to physical inspection, especially for large-scale solar panel which is installations where human inspection is labor-intensive, inconsistent, and less scalable. Integration with the robotic arms or unmanned aerial vehicles (UAVs) could be facilitate continuous monitoring and the repair procedures of reducing downtime and boosting energy output.

Future Enhancement:

Photographs with the minor dust accumulation can be added to the system to help in very early detection. The model may be extended to the detect dust at the level of individual solar cells or panels. The robustness can be improved by using the bigger and more varied dataset that includes different kinds of the dust and lighting. For improve accuracy and adaptability of CNNs and other deep learning techniques which can be applied. Autonomous inspection may be made possible by real-time integration with robotic arms or unmanned aerial vehicles. A comprehensive maintenance solution can be produced by integrating automated cleaning systems with detection.

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