Fault Identification in Solar PV Panels Using Thermal Image Processing Technique

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Abstract:- Photovoltaic (PV) module monitoringand upkeep are essential for a dependable and effective operation. Due to hotspots in PV modules brought on by a variety of flaws and operational issues, the dependability of the PV system may be put in jeopardy. Hotspots should be found and categorized from a monitoring perspective for later maintenance. In this study, hotspots are identified, assessed, and categorized using thermal pictures of PV modules and a machine learning technique. To do this, categorization is based on the texture and histogramof gradient (HOG) features of thermal pictures of PV modules. The machine learning method like Naive Bayes (nBayes) classifier is used to train the images in order to identify the hotspots and classifies them into defective and non-defective images.

Keywords:- *Hotspots, Monitoring, Photovoltaic (PV) Modules, Naive Bayes Classifier, Texture and Histogram of Gradients (HOG) Thermal Images.*

I. INTRODUCTION

Due in large part to the continuing decline in PV module prices and the growing interest in environmentally friendly energy sources, solar PV energy generation and utilization have increased significantly over the past few decades. The use of solar PV modules is widespread, with examples including utility-scale power plants, remote stand-alone telecommunication stations,residential rooftops, and nearly zero energy building facades. The International Energy Agency (IEA) estimates that there are currently more than 400 GWP of installed solar powersystems globally, with crystalline silicon (c-Si), both mono and poly, accounting for more than90%.

According to several studies that show lower performance ratios (PR) under actual conditions, the energy production of a PV system is typically significantly lower than the anticipated performance. Degradation in PV module performance that often begins after the first few years of operation and getting worse over time is frequently brought on by lower PRs. The inspection methods focus on isolating performancedeteriorations rather than assessing the dependability of PV modules, which requires an understanding of the different sorts of faults that can occur when the system is in use. Large PV facilities cannot be monitored using visual inspections and human interpretation. Many contemporary systems incorporate image processing to automate the procedure whereby broken PV modules may be promptly found or categorized into the appropriate categories.

II. LITERATURE SURVEY

Different approaches to fault detection and analysis, including monitoring systems, artificial intelligence based I and C analysis, voltage and current measurements, and power loss measurements, lack precise data and are not decentralized in the system for inverters and fault diagnosis [1]. Assessments of the fully operational power plants were made after evaluating the solar PV system's connections to the grid and its simulation using the MATLAB software [2]. Comparisons between the regular model and anticipated values of the proposed system were made using the output readings for the fault systemon PV from the various types of shading. A graph showing the noise for these outputs' detection times and a stability curve for the relevant data were also made [3].

The spectral information is supplemented by thetexture properties. HOG features are utilized for picture identification and image detection by storing the local gradients in the images [4]. Histogram equalization is carried out to increase the contrast to facilitate picture distinction [5]. Modelling a genuine PV system is extremely difficult since electrical characteristics differ greatly between PV systems due to variations in the location, physical layout, and PV module manufacture (including size, material, and ground connection) [6].

Numerous elements, including wear-and-tear issues, tracking errors for the maximum power point, electrical wire losses, production issues, and overheating, can have an impact on the energy losses and output power failures in the PV system. A PV system's output power may be reduced by these various factors by 50% [7]. Modern technologies and nondestructive testing techniques like the thermal image process are used to identify faults in solar PV modules. To achieve perfection for the deduction of the fault, a neural network classifier-based method is designed using various sets of criteria and collections of modules. [8].

Current and voltage are the two factors that have the biggest impact on a PV system's performance. The electrical signature of each defective module and array was repaired using a straightforward current-voltage analysis method that took into account the deformations generated on the I/V curves [9]. For the industrial control computer to identify each solar module individually, they must be treated as single cells. Then, for the various typesof issues, including a broken grid, fragmented cells, black fragments on solar cells, and cracks in the cells, several approaches are utilized to pinpoint theissue and determine the degree of faults present. It offers extremely precise and quick real-time processing [10]

III. PROPOSED SYSTEM

The proposed system consists of Thermal Camera which capture the image and process the image using MATLAB software and detects the fault in the solar panel. To efficiently monitor and classify solar PV modules, a machine learning- based technique is proposed. Essential features are extracted from the non-radiometric thermal images of PV modules and redundant information is removed, which forms the basis of the classification. The algorithm is trained using the multi-class density-based classifier, i.e., a Naive Bayes (nBayes) classifier, instead of a binary classifier. Notably, the nBayes classifier can solve the multi-class density-based classification problems, i.e., to calculate explicit probabilities for each hypothesis based on the Bayes theorem. In nBayes classifiers, the value of a specific feature is autonomous to the value of any other feature, givento the class variable. According to the training method, PV modules are categorized into three types:

- *Defective*
- *Non-Defective*

IV. WORKING

- *The Block Diagram for the Proposed System:*

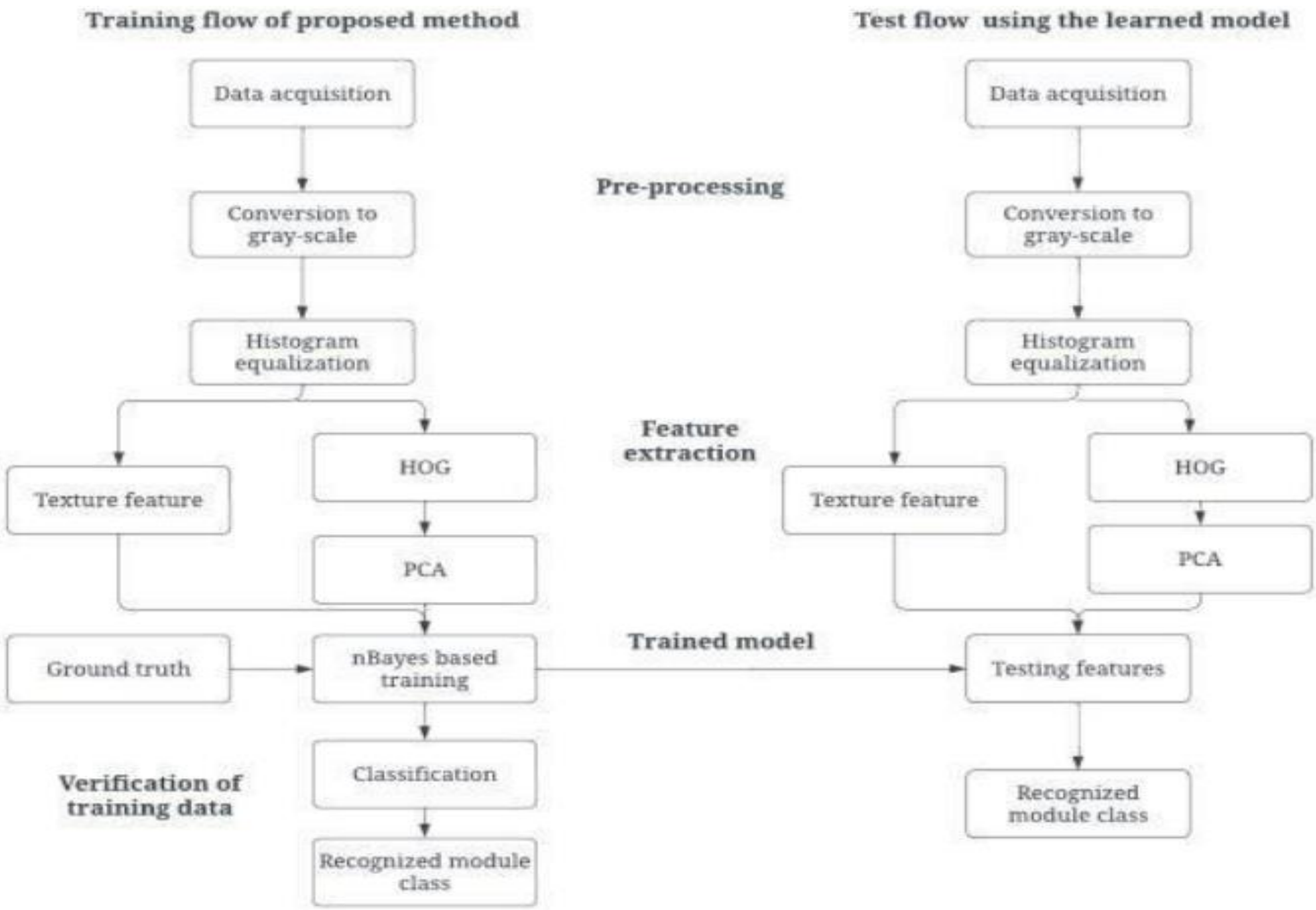

Fig 1 The Proposed System

➢ *Modules:*

- *Data Acquisition*
- *Pre-Processing*
- *Feature Extraction*
- *Training*
- *Classification*

➢ *Module Explanation:*

- *Data Acquisition*:

The FLIR thermal camera has captured non-enhanced and nonradiometric thermal photos of solar PV modules. Theacquired dataset was manually labelled and divided into the three classifications of Defective, NDH, and NDNH by the PV module.

- *Pre-Processing*:

Pre-processing is a necessary step to improve the textural information and dependability of the data gathered from thermal pictures of PV modules. The suggested n-Bayes- based classification approach uses the texture and HOG characteristics. The RGB image is preprocessed by making it a grayscale image to measure the amount of light that is present at each pixel in a single band of the electromagnetic spectrum. Additionally, to enhance the grayscale PV's contrast.

- *Feature Extraction*:

When the categorization is based on machine learning techniques, features are crucial. Then, from each thermal image of a PV module, the texture and HOG features are retrieved. For the purpose of identifying and categorizing spectrally diverse images, such as thermal images of PV modules, the texture feature is utilized to augment the spectral information. By storing the local gradients in the images, the HOG feature, on the other hand, is used for image identification and image detection. In this research, the feature descriptors for the categorization of solar PV modules are built using the two categories of characteristics. Which are:

✓ *Texture Features*
✓ *HOG Attributes*

$$Contrast = \sum_{i,j=0}^{N-1} (i-j)^2 \times m_{ij} \ldots\ldots\ldots\ldots (1)$$

$$Energy = (\sum_{i,j=0}^{N-1} m_{ij}^2)^{1/2} \ldots\ldots\ldots\ldots (2)$$

$$Homogenity = \sum_{i,j=0}^{N-1} \frac{m_{ij}}{1+|i-j|^2} \ldots\ldots\ldots\ldots (3)$$

$$Correlation = \sum_{i,j=0}^{N-1} \frac{(i-\mu)\times(j-\mu)\times(m_{ij})}{1+\sigma^2} \ldots\ldots\ldots (4)$$

In the following equation, i and j stand for the positions of pixels inside an image, mij is the value of those pixels, N stands for the number of grey levels in the image, is the mean, and 2 stands for the variance of the pixel values.

- *Training*:

Thermal pictures are used as training data for these three distinct types (Defective, NDH, and NDNH). In order to train the model, 4 the HOG and texture features are computed, resulting in a concatenated feature descriptor foreach training image.

- *Classifier*:

An n-Bayes-based multi-class density-based classifier from the library of pattern recognition tools is used to categorize solar PV modules into the groups of faulty, NDH,and NDNH. This classifier has several features, and each training PV thermal picture affects the probability of a given hypothesis. This allows the classifier to more effectively rule out any incompatible hypotheses. Combining these forecasts based on their confidence score also assigns a confidence percentage to the projections. Additionally, it explicitly resolves the problem of classifying PV modules into their appropriate groups by classifying each fresh thermal image of a PV module as a prediction function of several hypotheses that are weighted by their probabilities.

V. RESULTS AND DISCUSSION

The thermal images dataset was created using a solar panel of 12 volts rating and Seek Thermal Camera (CT-AAA). The small area of the solar panel was made inactive by covering it with a cardboard. This is conceptually the effect similar tothat of hotspot. The 200 images were taken, with 100images each of normal PV panels and hotspot images. 170images are used for training and 30 images for testing. The sample images are shown infigure 2.

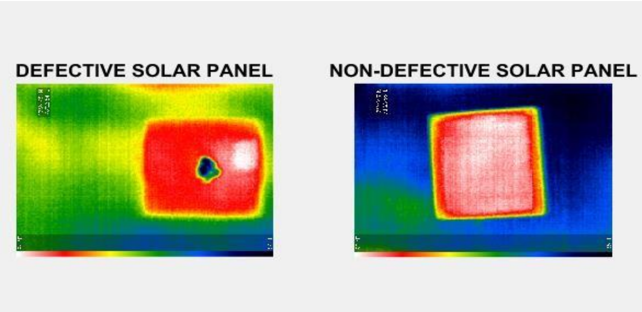

Fig 2 Thermal Images of Defective and Non-Defective Solar Panels

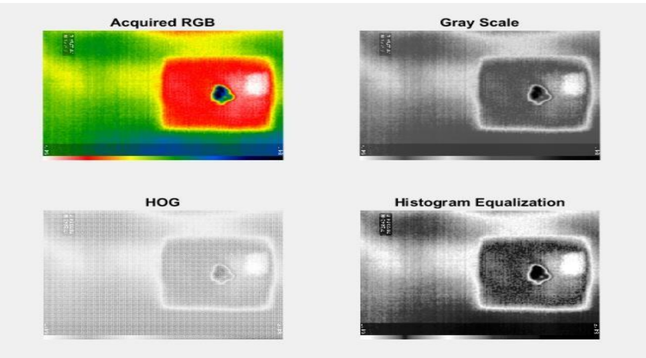

Fig 3 Pre-processing of a defective solar panelwhich includes, Gray scale image, HOG feature extraction and Histogram Equalization of an image.

- *The feature extraction of Contrast, Correlation, Energy and Homogeneity maps for Defective andNon-Defective solar panel are given in Figure 4 and Figure 5.*

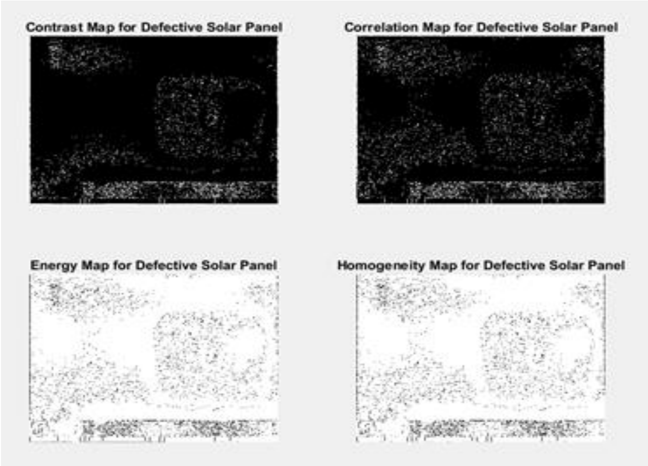

Fig 4 Feature extraction of Defective solar panel

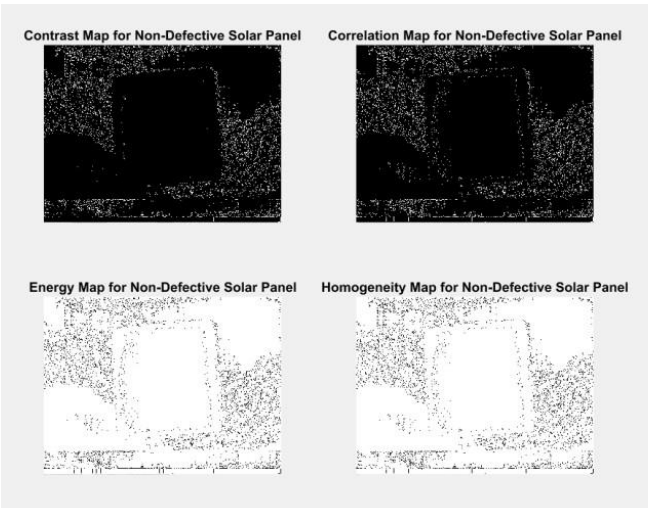

Fig 5 Feature extraction of Non-Defectivesolar panel

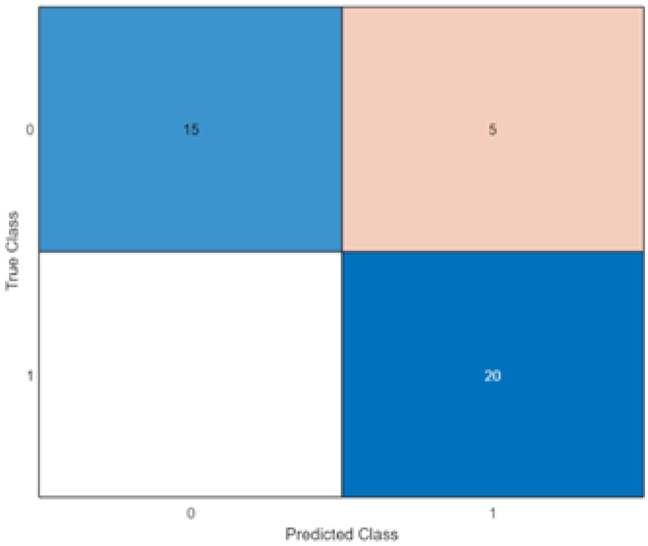

Fig 6 Confusion Matrix of Given Dataset

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