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HOTSPOT REVELATION IN SOLAR PANEL USING SPARSE RECONSTRUCTION AND EXTREME LEARNING MACHINE

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ABSTRACT

In today's world, solar panel is one of the major sources for generating power directly from the sunlight by using electronic processes and there is no greenhouse emission in photovoltaic cell as it does not require any other source of fuel like coal, natural gas, oil, nuclear power systems. Hotspot is one of the main causes of photovoltaic cell which occurs due to the dissipation of power in shaded cells. In the existing literature, the hotspot in solar panel is detected by using various algorithms and techniques but it does not improve accuracy, performance, temperature distribution, problem like overfitting and underfitting also exists. To overcome that, the proposed work deals with capturing the hotspot as thermal image through an infrared camera which is mainly used for temperature distribution. For identifying hotspot, the features like shade, correlation, contrast, energy, entropy, homogeneity, prominence, sparse are extracted using sparse reconstruction and GLCM algorithms. The features are given to the classification algorithm named as Extreme Learning Machine which gives the good generalization performance and improves accuracy higher when compared to other algorithms. The overfitting and underfitting problem can also be rectified by using these algorithms. Finally using extreme learning machine, the percentage of hotspot in photovoltaic cell can be identified.

Keywords: Photovoltaic cell; Hotspot; Sparse Reconstruction; GLCM; Extreme Learning Machine (ELM)

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1. INTRODUCTION

Nowadays, the use of solar photovoltaic energy has been realized by the people across the country. The important thing in using photovoltaic energy is, it gives access to countless people though there is more number of facilities in modern energy world [1]. As stated in the Renewables Global Status Report in 2015, the harness energy from the sun has been increased nowadays when compared to last few years. The total energy produced by the photovoltaic cell has raised from 3.7 Gigawatts in the year 2004 and increased to 177 gigawatts in the year 2014. In Philippines, solar Photovoltaic cell (PV) has been increased higher and many projects are introduced around the country. Especially in shopping Malls, residences, the establishment of solar PV has increased and installed [9]. The world largest solar power plant was located in China named as Longyangxia Dam Solar Park with the capacity of 850 MW. In India, the largest solar power plant is located in Kamuthi (Ramnad), TamilNadu which has capacity of 648MW. The average size of solar panel should be 65 inches by 39 inches or 5.4 feet by 3.25 feet. The solar panel should be faced towards south because India is located in Northern Hemisphere. The solar PV module is manufactured for past 20 to 25 years [10]. As there are no moving parts, the solar panel requires low maintenance and cost is also minimum [4]. Then the damages are occurred which starts out as a hotspot. In solar photovoltaic module, the defect named as Hotspot occurs when the normal operation of PV is affected. There are many reasons or conditions for occurrence of hotspot. The main reason is due to shading. Shading occurs due to branch of a tree, an antenna, dirt, a nearby building or anything that physically blocks the flow of current in solar PV module. With respective to single solar panel, the cells are connected in series. After the sunlight falls on cell, the flow of electron occur which produces current. Due to shaded cell, the current from good cells would be reduced. The higher voltages produce from good cell reverse bias by the bad cell. At this situation, there would be a large dissipation of power in the poor cell. The dissipation of the power in that area results in overheating or hotspots. If this happens continuously, the hotspot may lead to catch fire. If one cell is affected, the power output is reduced by as much as 33% of original power [1][8]. An existing defect crack or dent is another cause of hotspot. At this case, the load becomes more and current to this particular cell reverse biases and therefore the dissipation of power occurs which leads to the occurrence hotspot in a PV module. At this time the efficiency gets decreases as the output power decreases [7]. For detection of hotspot, the various hotspot detection techniques are discussed in existing literature. The proposed work mainly focuses to improve accuracy and performance. The features is extracted using GLCM and Sparse Reconstruction and it is fed into the classification algorithm namely Extreme Learning Machine (ELM) to classify the hotspot and to identify the percentage of hotspot in the affected area.

2. RELATED WORK

Yihua Hu et al [1] define PV modules with respect to levels of faults and its terminal characteristics based on the fault categories. By analyzing the different faults that have been done analytically, experimentally. Through the simulations, and experimental tests, this work identifies Photovoltaics cells thermal and electrical characterization that occurs in many fault algorithms. Additionally, the fault is diagnosed by incorporating the maximum power tracking algorithm (MPPT). This algorithm is mainly used after the hotspot has occurred, to extract the loss power at the most. The operating point of PV string can be shifted by using MPPT algorithm.

Ahteshamul Haque et al [2] identified the hotspots or faults in PV modules and also it focuses to remove anomalies. For removing anomalies, the special tool is used. The proposed work uses a methodology called Neural Network (NN) classifier for identifying the type and location of occurring faults. It transfers a characteristic that is I-V data of the faulty PV module for the diagnosis which adapts multilayer perceptron.

A.M.Salazar et al [3] dealt with detection of degradation of Photovoltaic systems and to specify the particular cell or area which is used to produce hotspots due to overheating. The large area can be accessed via thermography. The images are taken for an operating PV module using an infrared camera. These are implemented by using MATLAB.

J.A. Tsanakas et al [4] used a diagnostic tool named as Canny Edge Detection operator for module related faults and it is one of the standard thermal image processing techniques. The module related faults leads to hotspot heating effects. For defective PV modules from several fields, intended techniques and infrared thermographic measurements are applied on thermal images during this study.

Stephen C. Yang et al [5] proposed the inception of hotspot can be diagnosed by using input panel-string sensor data. Hotspot is detected by using Bayesian Maximum A Posterior Probability (MAP) inference engine. Equalization of unknown quantity and posterior distribution is an estimate of Maximum Posterior probability. This model has three ingredients: spline-based approximations which consist of state variables. A path-integral based Bayesian MAP module is used for detecting hotspots or other degradation or fault had be occurred. In this network, the data was generated from a model in which at least three variables are correlated to each other at this time Bayesian network is not able show the relationship between them.

Bruce Mehrdadi et al [6] created a system capable to detect the possible faults in PV systems the work proposed artificial neural network and radial basis function and also fuzzy logic interface. Four different Artificial Neural Networks (ANN) are compared using faulty conditions affecting the examined PV plant. By using this algorithm, the several defects can be identified such as faulty in a PV module in a PV string, faulty PV string, faulty MPPT, and also the partial shading conditions effects of PV system. The next method consist of two types of fuzzy logic interface systems namely Mamdani and Sugeno. Mamdani is well suited for user input whereas Sugeno is mainly used for mathematical analysis. By using four ANN networks and two fuzzy logic controller, the hotspot is detected. For more accuracy, some more fuzzy grades are needed and also lower speed and take longer runtime of the system.

AlessiaSaggese et al [7] identified the detection of hotspot in photovoltaic cell by camera on drones. It mainly used for computing false positive, true positive, recall, precision by extracting the lines of the images by using Hough transform and it is further used to align the image. The Hough transform is one of the feature extraction technique used in image analysis. The second is to find the panels, the work follows three steps: first one is to consider that border of the panel would be the vertical lines. The second one is consider same for the horizontal lines. The third one would be for whole grid there would be exactly four borders such as two vertical lines and two horizontal lines. It uses the model based approach traditionally combined with color based approach. In such a way that, the hotspot is detected for higher temperature distribution.

Hongtian Chen and Bin Jiang [8] show the unknown information in the test data. The method used in this paper is space-to-space projection mainly used for identifying hotspot. This method is mainly used for preserving geometrical structure. It mainly focuses on three key features: the first thing is this method does not implementation of any mathematical model and physical knowledge. Next, it deals with computing a high- efficiency in detecting online phase and also the dynamic behaviour is captured because of local structure of sampling time is regarded.

Erees Queen B. Macabebe et al [9] focused on the growth of photovoltaic manufacturing industry is enormous in technological world. It focuses to detect the hotspot by applying two machine learning algorithm namely K-means color quantization for preprocessing and density-based spatial clustering with noise for processing the image captured. During pre-processing, the image captured was converted to float and normalised for faster convergence. After that the image is transformed to 2D array. Then the k–means algorithm is executed. This result is given as an input for processing which is carried out by DBSCAN. The algorithm requires two parameters: one is to find how close the points to each other and another finding minimum number of points in that particular area. It is mainly used for segmenting the image to show the affected area. While executing DBSCAN, the total number of clusters can also be known for a particular image.

Peter Mather et al [10] proposed the fuzzy logic systems more in photovoltaic systems. The algorithm mainly identifies the fault in a PV modules occurring in solar plant using theoretical curves modelling algorithm and fuzzy logic classification system especially for classifying the images. Using this algorithm, four different scenarios are tested: the first one is a faulty PV module with partial shading condition. The second is two faulty PV modules with partial shading conditions and third is three faulty PV modules with partial shading conditions and finally the four PV modules with partial shading conditions. For each test the measured data is plotted and compared with the theoretical curve limits. After classifying the images, the detection of hotspot was carried out by evaluating two different PV modules which contain different hotspots.

3. PROPOSED SYSTEM

The main objective of the proposed system is to detect the percentage of hotspot that occurs in the solar panel with good accuracy, less training speed and it can be able to produce good generalization performance which learns thousands times faster than networks trained using backpropagation. The proposed work is carried with the help of three categories. The first is to collect the affected images of photovoltaic cell, which are captured using thermal camera. Then, the images are preprocessed to remove noises in the data. Based on the filtered image, the necessary features are extracted. These features are given to the classification algorithm for detecting hotspot and also identify the percentage of hotspot is as shown in Figure 1.

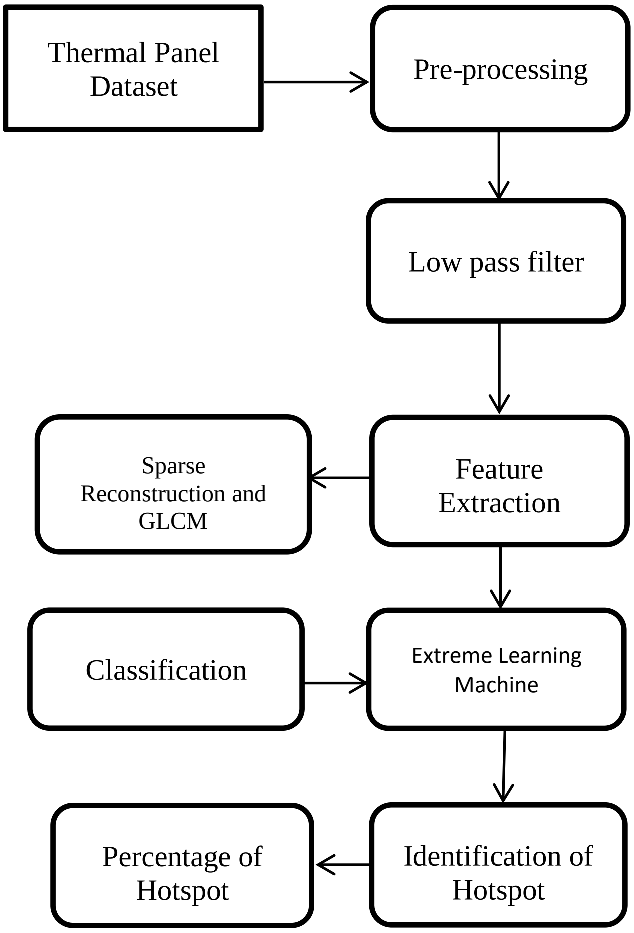


Figure 1 Architecture for detection of hotspot in Photovoltaic cell

3.1. Data Preprocessing

Preprocessing is an important step to remove unnecessary information and noises from the input image. This step will improve the image quality. The main step involved in data preprocessing is data cleaning which includes missing of data, removing noise and data reduction. In this work, the data is preprocessed using a Low pass filter algorithm.

A Low Pass Filter

A low-pass filter is mainly used to pass a certain band of frequencies from it. Low pass filter removes high frequency component and keep low frequency component. It is mainly used for smoothen the image. The signal with high frequency component reduction is used for identifying cost of low pass filtering. Low Pass Filters (LPF) is to allow the frequency below the cut-off range. The low pass filter has several forms such as Ideal, Butterworth and Gaussian filters. Figure 2 describes the steps to be carried out for removing noise and produce enhanced image.

Ideal Low Pass Filter

The transformation function of Ideal LPF is given by equation (1).

$$H(u,v)=\begin{cases} 1 & D(u,v) \leq D0 \\ 0 & D(u,v) > D0 \end{cases} \quad (1)$$

where H(u,v) is filters represented in frequency domain.

D_0 is non-negative integer.

D(u,v) is the distance of the point u,v to the origin of image.

Let the dimension of image is m*n. So, the distance is calculated using equation (2).

$$D(u,v)=[(u-m/2)^2+(v-n/2)^2]^{1/2} \qquad (2)$$

Gaussian Low Pass Filter

The Gaussian filter is mainly used to reduce contrast and blur the image for reducing noise.

Blurring is mainly used for smoothening an image because the edges are not observed. It removes the low intensity edges.

The transformation function of Gaussian LPF is given by equation (3).

$$H(u,v)=e^{-D^2(u,v)/2D_0^2} \qquad (3)$$

Butterworth Low Pass Filter

For a specified pass band with order n, the frequency domain filter should be designed in such a way that it should remove noise with minimal loss of signal components.

The transformation function of Butterworth LPF is given by equation (4).

$$H(u,v)=\frac{1}{1+\left[\frac{D(u,v)}{D_0}\right]^{2n}} \qquad (4)$$

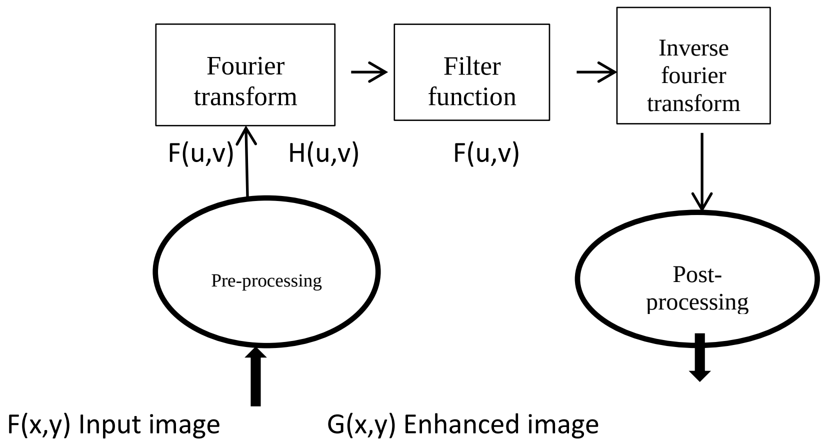


Figure 2 Working flow of Low Pass Filter

3.2. Feature Extraction

Feature vector is the one which represents the part of an image efficiently. For an image, find the homogenous pixel that is the purpose of feature extraction. In image processing, algorithms are used to detect various desired portions (features) of a digitized image. The identification of similar pixels from the image can be used for fast identification of hotspot part in an image. The necessary features are extracted using sparse reconstruction and GLCM algorithms.

Gray Level Co-Occurrence Matrix Features

Gray level co-occurrence matrix functions are mainly used to find the texture of an image. This is done by calculating the frequent pair of pixels within the specific values in an image. In other words, it tabulates different combinations of gray level that occur in the image. Second order statistical features can be extracted using GLCM. The features extracted through GLCM are correlation, contrast, prominence, cluster shade, dissimilarity, energy, entropy, homogeneity is as shown in Figure 3.

Correlation

Correlation is the measure of how the intensity of the pixel is correlated with its neighbor pixel in the whole image. The range of values for correlation lies between -1 to 1. If the image is positively correlated, then the value should be 1. If the image is negatively correlated, then the value should be -1. If the image is constant, then the value should be NaN for that particular image. The correlation feature is extracted using equation (5).

$$\text{Correlation n}=\frac{\sum_i \sum_j (i*j) G(i,j) - \mu i \mu j}{\sigma i \sigma j} \quad (5)$$

Contrast

Contrast is measure of intensity pf the particular pixel over the other pixel in the entire image. The contrast can also be termed as inertia or variance. For a contrast image, the value should be 0. The low contrast image can be identified by calculating the details present in that image. In simple words, the contrast is comparison between blacks and white that occurs in the image. The contrast feature is extracted using equation (6).

$$\text{Contrast}= \sum_i \sum_j (i-j)^2 \text{G(i, j)} \quad (6)$$

In an image, if there is large amount of variation, then the contrast would be high.

Prominence

Generally, the prominence refers as the importance. The image is less uniformity, if the prominence value is high. The GLCM matrix has the peak values if the prominence is low. There will be small variance in a gray-scale if the prominence value is low. The prominence feature is extracted using equation (7).

$$\text{Prominence}=\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \left(i+j-u_x-u_y\right)^4 G(i,j) \quad (7)$$

Entropy

For image compression, the amount of information needed for the image is calculated by using entropy function. The entropy value will be low for homogenous image and entropy value will be high for heterogeneous image which is calculated using equation (8). It mainly focuses on intensity distribution.

$$\text{Entropy}=-\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} G(i,j)\log(G(i,j)) \quad (8)$$

Energy

Energy measures the sum of squared elements in Gray-level co-occurrence matrix (GLCM). For a constant image, the value should be 1. For energy, the value ranges from 0 to 1 is depicted using equation (9).

$$\text{Energy}=\sum_{i,j} G(i,j)^2 \quad (9)$$

Variance

The elements which are differs from the average value are assigned with high weights. If the mean value differs, the variance gets increases. The variance feature is extracted using equation (10).

$$\text{Variance}=\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} (i-u_x)^2 G(i,j) + \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \left(j-u_y\right)^2 G(i,j) \quad (10)$$

Inverse Difference Moment (IDM)

The homogeneity of an image can be calculated using IDM. This value gets increases while the gray-scale values are close and the pixel pair co-occurrence also gets increased. For homogenous image, the IDM value would be low or else the IDM value would be high is given by equation (11).

$$\text{IDM}=\sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{1}{1+(i-j)^2} G(i,j) \quad (11)$$

Shade

In the GLCM matrix, the skewness can be calculated by using shade functions which is shown in equation (12). If the shade is high, then the image denotes asymmetry.

$$\text{Shade= Shade}=sgn(A)|A|^{1/3} \tag{12}$$

Where $A=\sum_{i,j=0}^{N-1}\frac{(i+j-2\mu)^3 Gij}{\sigma^3\left(\sqrt{2(1+C)}\right)^3}$; Sgn =Sign of a real number

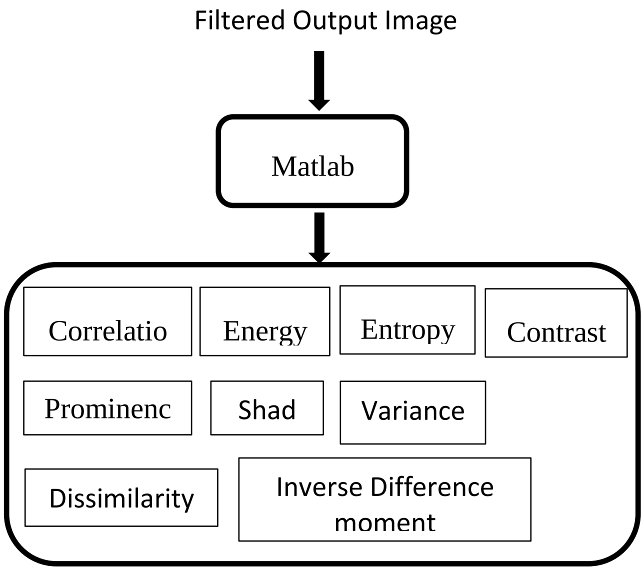


Figure 3 GLCM Features extracted for an image

Sparse Reconstruction

Sparse reconstruction is an additional feature that is combined with GLCM to get more accuracy and also to overcome overfitting problems. Using sparse reconstruction, the wavelet feature can be extracted which gives accurate results in different orientations. In this, there are many techniques such that this work deals with Least Absolute Shrinkage and Selection Operator (LASSO) technique.

Consider m*n matrix A with n-dimensional vector, the observation and estimation difference should be minimized that is used for restoration is expressed as equation (13).

$$\min_x \frac{1}{2}||y-Ax||_2^2 \tag{13}$$

where y is m-dimensional vector y and product of noisy observations Ax.

By using sparse reconstruction, the algorithm provides an accurate result in different orientations. It also solves overfitting and problems.

3.3. Classification

Machine learning (ML) is the advancement of artificial intelligence. In ML, the system has the ability to learn by itself without being explicitly programmed. For classifying positive and negative values, the inputs are assigned by some weights and the output separates into two values. In this work, the algorithm named as Extreme Learning machine is used for classifying the affected part that is hotspot area in the solar panel. By using this algorithm, the percentage of hotspot can also be identified.

Extreme Learning Machine

ELM is a neural network and is a fast learning algorithm. It is a single hidden layer feed forward neural network (SFLN) that is, it does not contain any cycles and data enters through the input layer and passes through the network layer by layer. This is continued until it reaches output layer. In ELM, the classification problem can be solved in a lesser time because the weights and biases assigned to the hidden neurons are randomly generated is as shown in Figure 4.

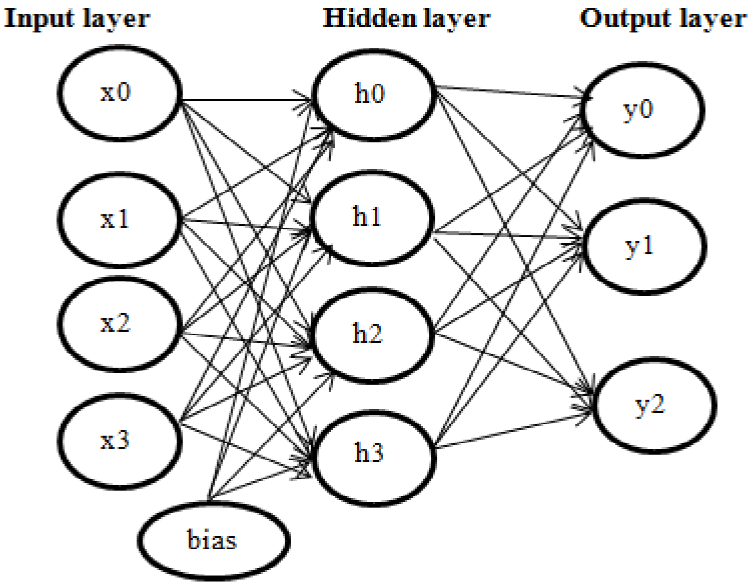


Figure 4 Structure of ELM

3.4. Three Step Procedure

1. For a hidden layer, assign weights and biases randomly. No iteration is required.

2. To compute the output matrix for hidden layer, progress the inputs with the hidden parameters.

3. Finally, the output weights can be identified by taking inverse of the hidden output matrix. This is done by using Moore-Penrose generalized matrix that is, solving a set of linear equations.

For a set of d-dimensional vectors defined for i=1,2,…, N training samples, the SLFN with L hidden neurons is mathematically expressed in equation (14).

$$f_l(x)=\sum_{i=1}^{L} h_i(x)\beta_i = h(x)\beta \qquad (14)$$

β is the output weight matrix and $h_1, h_2 \dots$ are hidden neuron outputs. $h_i(x)$ is the ith hidden neuron.

For hidden neurons, the output function $h_i(x)$ is be calculated using equation (15).

$$h_i(x)=G(a_i, b_i, x) \text{ where } a_i \in R_d,\ b_i \in R \qquad (15)$$

$G(a_i, b_i, x)$, which is defined using hidden neuron parameters(a,b) that must satisfy the ELM approximation theorem.

The sigmoid equation, which has been adopted widely in neural network-based modelling, was used for developing the ELM model is expressed in equation (16).

$$\text{Log sigmoid} = G(a,b,x) = \frac{1}{1+exp(-ax+b)} \qquad (16)$$

While solving the weights connecting the hidden nodes, the error should be minimized and output layer (β) is identified by using least square fitting which is shown in equation (17).

$$\min_{\beta \in R^{l*m}} ||H\beta - T||^2 \qquad (17)$$

H is the randomized hidden layer output matrix is depicted in equation (18).

$$\mathrm{H}=\begin{bmatrix} g(x1) \\ \vdots \\ g(xN) \end{bmatrix}=\begin{bmatrix} g_1(a_1x_1+b_1) & \cdots & g_L(a_Lx_1+b_L) \\ \vdots & \vdots & \vdots \\ g_1(a_Nx_N+b_1) & \cdots & g_L(a_Lx_N+b_L) \end{bmatrix} \qquad (18)$$

Target matrix in the data training period is expressed in equation (19).

$$\mathrm{T}=\begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}=\begin{bmatrix} t_{11} & \cdots & t_{1m} \\ \vdots & \ddots & \vdots \\ t_{N1} & \cdots & t_{Nm} \end{bmatrix} \qquad (19)$$

Linear equations are used for solving an optimal solutions which is stated in equation (20).

$$B^*=H^+T \qquad (20)$$

ELM is preferred over other algorithm because it solves overfitting problems and it does not require any iteration. Normally, trial and error method is used for identifying hidden neurons. But in ELM, the hidden neurons are randomly assigned so it takes less time. The local minima issues can also be rectified using ELM.

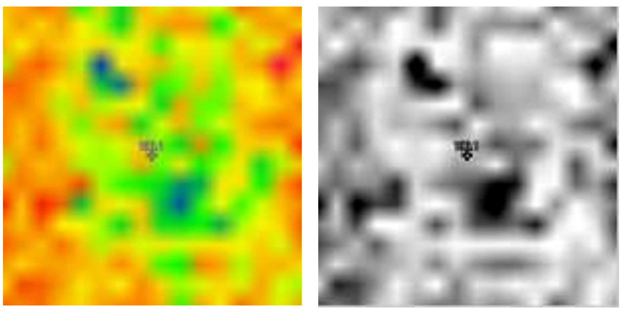
4. RESULTS AND DISCUSSION

For identifying hotspot or partial shading in photovoltaic cell, the thermal images are taken using FLIR infrared camera is as shown in Figure 5 (a). By using normal camera images, all the affected part cannot be identified.

4.1. Pre-processing using Low Pass Filter

The work is implemented by loading an image as shown in Figure 5 (a) and is converted to the grey scale image because in image processing, the color image cannot be processed. So it should be converted to a grey format. In grey image, based on the variations the image would be brighter or lighter.

After that, the adjusted image would be displayed by performing fourier transform and inverse fourier transform by creating 5% width of fourier spectrum and convert it into the spacial domain. Computing the absolute magnitude and it uses to log to brighten display. The adjusted noise free image is displayed is as shown in Figure 5 (b).



(a) (b)

Figure 5 (a) Thermal image of PV module and (b) its filtered image using LPF

4.2. Feature extraction using GLCM and Sparse Reconstruction

For an image, the maximum and minimum values for each GLCM and sparse features are extracted. The features are listed below that is

stats=

$$\begin{bmatrix} 1.289897798742138e-01 & 1.491745283018868e-01 \\ 9.273959022593070e-01 & 9.160737039213945e-01 \\ 3.728921362785116e+01 & 3.615752314500804e+01 \\ -4.128391434980077e+00 & -4.011832742678788e+00 \\ 9.825078616352205e-02 & 1.151336477987422e-01 \\ 2.590205871164363e-01 & 2.533152071883899e-01 \\ 1.664605193642012e+00 & 1.705979317305390e+00 \\ 9.534415478062296e-01 & 9.451953475965861e-01 \\ 1.051705257486999e+02 & 1.045483744214210e+02 \\ 1.586289684776324e+00 & 1.616565932589659e+00 \\ 1.289897798742139e-01 & 1.491745283018868e-01 \\ 3.205483779813244e-01 & 3.571814085196259e-01 \\ -7.247046783519865e-01 & -6.931406481444347e01 \\ 9.893422636936790e-01 & 9.874904851437869e-01] \\ 9.981864721691459e-01 & 9.979017057631109e-01 \end{bmatrix}$$

4.3. Classification using Extreme Learning Machine

The extracted features are given to an Extreme Learning Machine, which will identify the area of hotspot. It also identifies the percentage of hotspot that occurred in the image.

Figure 6 Identification of Hotspot

Based on this affected area, the percentage of hotspot will be identified with good classification accuracy in less amount of time. This can overcome overfitting problems and no iteration is required for whole process.

5. CONCLUSION

In this work, the detection of hotspots in photovoltaic cell is identified with good classification accuracy. By using this technique, the training time is reduced for the datasets and it overcomes the overfitting problems. This done by taking panel images and preprocesses to remove noise and features are extracted using GLCM and sparse reconstruction algorithms. Finally, the percentage of hotspot is identified using Extreme Learning Machine algorithm. ELM has a better understanding; weights are randomly assigned since iteration is not required; it is less complex and good accuracy in less time.

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