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Solar PV's Micro Crack and Hotspots Detection Technique using NN and SVM

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ABSTRACT For lifelong and reliable operation, advanced solar photovoltaic (PV) equipment is designed to minimize the faults. Irrespectively, the panel degradation makes the fault inevitable. Thus, the quick detection and classification of panel degradation is pivotal. Among various problems that promote panel degradation, hot spots and micro-cracks are the prominent reliability problems which affect the PV performance. When these types of faults occur in a solar cell, the panel gets heated up and it reduces the power generation hence its efficiency considerably. In this study, the effect of the hotspot is studied and a comparative fault detection method is proposed to detect different PV modules affected by micro-cracks and hotspots. The classification process is accomplished by utilizing Feed Forward Back Propagation Neural Network technique and Support Vector Machine (SVM) techniques. Six input parameters like percentage of power loss (PPL), Open-circuit voltage (V_{OC}), Short circuit current (I_{SC}), Irradiance (I_{RR}), Panel temperature and Internal impedance (Z) are accounted to detect the faults. Experimental investigation and simulations using MATLAB are carried out to detect five categories of faulty and healthy panels. Both methods exhibited a promising result with an average accuracy of 87% for feed-forward back propagation neural network and 99% SVM technique which exposes the potential of this proposed technique.

INDEX TERMS Binary tree, Feed Forward Back Propagation Neural Network, Hot-spotting, Micro crack, PV module, Support Vector Machine

I. INTRODUCTION

In photovoltaic (PV) panels, hot-spotting is a solidity problem. It can be characterized when the adjacent solar cells heat up to a remarkable level and decrease the optimum power generation of the PV panel (Dhimish et al., 2018a). Hot spotting arises when a single cell or group of cells operate at reverse bias condition or peculiar inflated temperature levels (Mazumdar et al., 2014; Pannebakker et al., 2017). Hotspots are predominately caused by following reasons – non-uniform current density, variations in shading, improper soldering, and package failure (Akram et al., 2020). Due to the hotspots, PV degradation is enhanced and a high probability for the occurrence of permanent damage to PV panels prevails (Simon and Meyer, 2010). Another solidity problem that affects the PV panels is discontinuation [6], Maximum Power Point Tracking (MPPT) faults (Rakhshan et al., 2018; Dhimish et al., 2019; Pendem et al., 2020; Manoharan et al., 2020; Pradhan et al., 2020), micro-cracks (Dimish et al., 2017) and variations in the wind speed and humidity (Stoichkov et al., 2018). The above-mentioned problems affect the performance of output power in a PV panel but, the parameters such as temperature coefficient will decrease its annual energy production. Ultimately, these studies only state the effect of hot-spotting in PV panels but do not focus on other issues. For obtaining the maximum output from the PV system over the lifetime, systematic maintenance and perpetual inspection are mandatory (Dhoke et al., 2018). Since manual inspection is impracticable in large scale power plants, automatic inspection is effective to detect defective panels using various methodologies. These methodologies have broadly classified into two parts as (i) Based on Electrical signal (ii) Based on image processing (Photoluminescence, Electroluminescence, Fluorescence, Infrared Thermography techniques). In the electrical signal-based fault detection category, the modulation of PV module temperature is achieved the by altering the electrical behaviour in severe and mild defective regions (Waqar Akram et al., 2019). In the image processing-based fault detection methodologies, neural network and machine learning algorithms are involved. Naïve Bayes classifier algorithm detects the degradation in PV module as faulty and non-faulty instead of detecting the individual faults (Niazi et al., 2019). Recently, PV inspection using Infra-Red (IR) camera has become a common practice to observe the PV hotspots (Hu et al., 2014). Defective regions in Infra-Red images are visualized by variation in colours and difference in brightness. However, the effects of hotspot on the performance of PV systems have not been noticeably addressed. This initiates the researchers to analyze the need for an approved mechanism to eliminate the hot-spotting and detailed specification for approval criterion in monetary structure.

In general, an approved mechanism to mitigate hot-spotting is accomplished by adopting bypass diodes. When these diodes are connected within the PV module, it may reach the excess reverse voltage level across the hot-spotted solar cells. This mechanism will boost the short circuit current and open-circuit voltage of the affected PV panel (Acciari et al., 2011; Kim et al., 2016; Dhimish et al., 2018b). Since it can be adverse in terms of power dissipation, it is uncharacteristic. Moreover, it increases the cost due to the use of additional bypass diodes (Manganiello et al., 2015). Another literature (Garoudja et al., 2017) showcased that a one diode model (ODM) based EWMA (Exponentially Weighted Mean Average) chart to the statistical fault detection in actual PV systems. Furthermore, a new MPPT technique is suggested by Coppola et al. (2012) and Olalla et al. (2018) to mitigate the hotspots in a PV module. It offers a predicted decrease of 20°C in small or medium hot-spotting regions. Besides, Kim and Krein (2015) have pointed the ineffectiveness of the typical bypass diodes and suggested that a switch is to be connected in series, which is suitable to interpolate the flow of current during the bypass activation process. Anyhow, this solution requires a modified convoluted electronic-based design. Dhimish et al. (2018c) proposed a hot-spot mitigation technique by joining few MOSFETs to the PV panels to rectify the hot-spotted PV solar string. However, the overall effect of PV hotspots on output power is not discussed. By using the infrared images, the Support Vector Machine system is employed in (Ali et al., 2020) to point out only three different classes' i.e. healthy, non-faulty hotspot and faulty hotspot. In the study authored by Dhimish and Badran (2019), the impact of PV hot-spotting using fuzzy systems was discussed. Certainly, the PV module affected only by hotspots will be accurately identified with an accuracy of 96.7%. Many techniques are available to mitigate the faults and hot spots (Winston, 2020; Winston, 2019), hence detection of fault and hotspots with high accuracy is the need of the hour. The above-mentioned literature mainly focuses on the hotspot fault only. Even though micro-crack faults are the small fissure occur in solar panel making it difficult to inspect with the naked eye, these faults should be taken into concern since it has a negative impact on the lifetime and performance of solar PV system. The proposed work deals with identifying hotspots as well as micro-cracks in the PV panel. Most of the article uses very complex techniques to find the faults in the PV panel. This technique is very simple and more efficient when compared with conventional intelligence techniques.

The primary objective of this proposed work is to study and investigate the effect of PV hot-spotting and micro-cracks faults. For this investigation, 10W PV modules are considered for experimentation. Though this study is conducted for a small panel at a particular geographical location, the proposed technique can be implemented for any panels at any locality. Since panel temperature, percentage of power loss and the internal impedance of the panel are considered in this study, the investigation can be extended to any PV modules affected by various environmental conditions and panel temperature. The secondary objective of this work is to develop an appropriate PV hot-spot fault detection algorithm using the ANN and SVM classification tool. Finally, the performance of both fault detection algorithms is tested and compared to find the best methodology. Thus, the different PV modules affected by various types of hot spots and micro-cracks faults are detected.

The study is structured as follows: Section 2 describes the proposed methodology and investigations, while section 3 presents the proposed ANN-based machine learning-based detection algorithm. The results of the proposed detection method are evaluated in Section 4 and finally, the conclusions are drawn in Section 5.

II. PROPOSED METHODOLOGY

This section details the methodology utilized to meet the objectives.

A. INVESTIGATION OF PV MODULES

The investigated PV panels are of Polycrystalline silicon (Poly-Si) type. Each panel has a capacity of 10 W. The categories of examined PV modules are shown in Fig.1. They are classified as healthy, one hotspot, two hotspots, more than two hotspots and micro cracks. The panels are mounted at the terrace of the institutional building, KCET, Virudhunagar, Tamil Nadu, India. After installation, the data collection was done by investigating the panels. A few measuring instruments such as voltmeter, ammeter, tong-

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tester, PCE-EM 886, and thermal imaging camera are utilized in this process. The measuring instruments are calibrated before it is subjected to various measurements to achieve high accuracy and tolerant rate. Solar irradiation and panel temperature were measured for various time intervals as our method can be extensively used for any set of environmental conditions. The panel specifications are given in Table I.

Before collecting the data, certain factors and processes are to be considered for conducting the investigation are listed below:

(i) The parameters are measured during a non-shading sunny day.
(ii) Solar panels with a set of hot spots and micro-cracks are created manually.
(iii) All these panels are inspected using IR cameras to identify the number of hot spots and locate the points where the failure occurs.
(iv) Few healthy panels are also considered to compare the data provided by hot-spotted modules and adjacent healthy modules.

The instruments and sensors within the accuracy of 95% and above are only considered to eliminate the imprecise data. By inspecting the hot spots using a thermal imaging camera (Coppola et al., 2012), three different types of hot-spots conditions were considered as shown in Fig. 2.

The procedure to detect the respective outcomes is discussed in the next section. The parameters such as Percentage of Power Loss (PPL) and Impedance (Z) in each faulted type PV modules are used to find the outcomes.

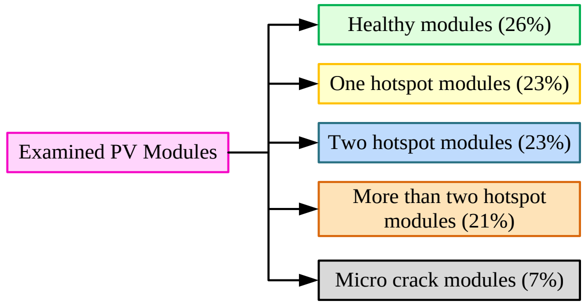

FIGURE 1. **Categories of Examined PV modules**

TABLE I
SPECIFICATIONS OF INVESTIGATED PV MODULE

PARAMETERS at STC	VALUES
Open Circuit Voltage (V_{oc})	**10.8 V**
Short Circuit Current (I_{sc})	**1.25 A**
Maximum Power Point Voltage (V_{mpp})	**9 V**
Maximum Power Point Current (I_{mpp})	**1.11 A**
Maximum Power (P_m)	**10 W**
Number of Cells in Series (N_s)	**18**
Nominal Cell Operating Temp (NOCT)	**45^{0}C**

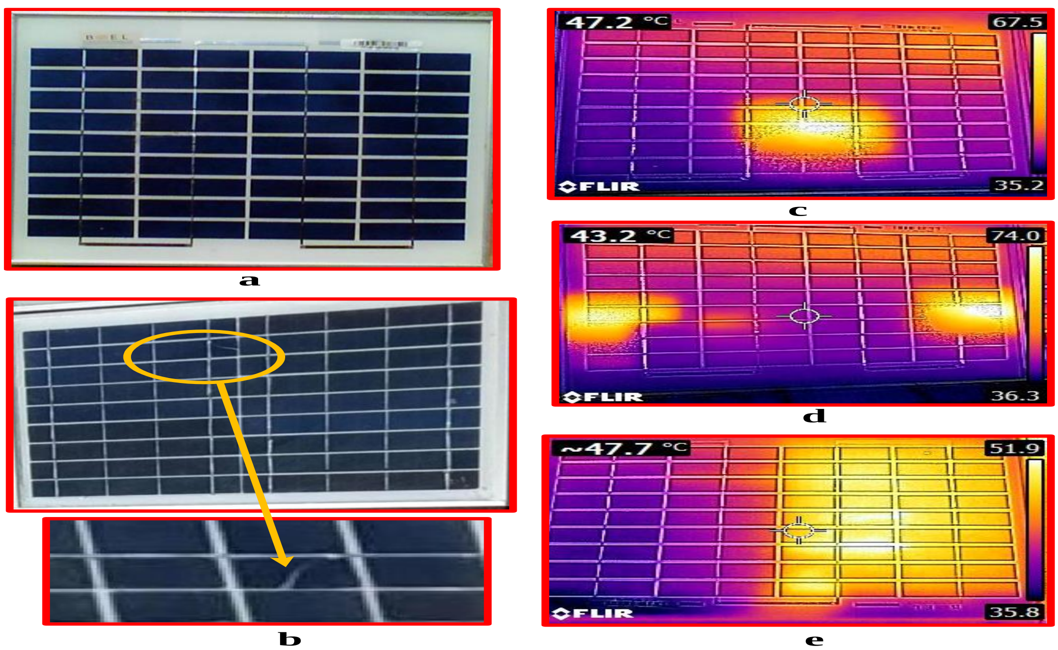

FIGURE 2. **PV modules examined under different conditions (a) Healthy (b) Micro-cracked (c) One hot-spotted (d) Two hot-spotted (e) More than two hot-spotted.**

B. ESTIMATION OF PERCENTAGE OF POWER LOSS (PPL) AND OUTPUT IMPEDANCE (Z)

Here, a technique is employed to estimate the PPL from the output power of hot-spotted PV modules. Accordingly, the calculations are done with its respective solar irradiance and panel temperature for an equal interval of time. Principally, the output power of the hot-spotted PV module is measured. Then the measured power is divided by the average output power measured from the adjacent healthy PV modules. The

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average output power from the adjacent healthy PV module is calculated using (1).

$$P_{Hav} = \frac{\sum_{i=1}^{n} \dot{P}V\ module\ power}{n} \quad (1)$$

The ratio of change in output voltage to the change in load current is known as output impedance. It is denoted using the symbol Z. The output impedance of the PV module is inversely proportional to the output current flowing from the PV module. In an electrical network, it is a measure of the opposition to the flow of current. The impedance is determined in terms of Ohms law (2),

$$Z = \frac{V_{oc}}{I_{sc}} \quad (2)$$

Where, V_{oc} is the open-circuit voltage in volts.
I_{sc} is the short circuit current in ampere.
Z is the output impedance in ohms.

The summary of the threshold (min to max) values is shown in Table II. In which, PPL, Voc, I_{sc}, I_{rr}, Z and temperature parameters are tabulated for all types of faults in the PV module. It can be noticed from Table II when the number of hot spots increases, PPL increases, V_{OC}, and I_{SC} reduces with a higher degree but, Z increases with a higher degree.

C. ANALYSIS OF PPL, V_{OC}, I_{SC}, I_{RR}, Z, TEMPERATURE PARAMETERS

From the analysis of the threshold values for all types of faults, only a minimum drop of PPL occurs in the PV module affected by micro-cracks. Also, an average PPL is equal to 10.47%. Furthermore, in the PV module with one hotspot case, an average PPL is 10.56 % and for two hot spot cases, it is 13.67 %. Also, for the PV module affected by more than two hotspots category, an average PPL is 19.23%. Thus, the result reveals that, if the number of hot spots in a PV module increases, then PPL also increases. These results are obtained from 93% of hot-spotted PV modules and 7% of micro-crack PV modules. Interestingly, when the hotspot of the PV module increases, the panel will suffer a great drop in its output power, therefore we can experience the increase of PPL. All the formulated PPL data are required to train the classifiers while detecting the type of fault that occurred in the PV module. Usually, the output impedance parameter is the resistance offered to the flow of current from the voltage source and it gets affected during the fault condition.

While analyzing the impedance of the investigated PV panels, it is well known that there is an increase in impedance for an increase in the number of hot spots or cases of micro cracks. For the PV modules in a healthy condition, average impedance is equal to 15.63%. Likewise, average impedance of PV modules affected by one hot spot is 17.19% and for two hot spotted solar cells is 13.67%. Similarly, for more than two hot-spotted PV modules, an average impedance is 19.23%. Comparatively, there is high output impedance during internal bus failure. The obtained output impedance of the PV panels during the faulted condition is used to train the FFBPNN and SVM classifiers. The average irradiation and temperature values (36.65^{0}C and 532 W/m^2) in micro cracked modules are notably less compared with healthy and other hot spotted modules.

Additionally, the parameters like open circuit voltage 'V_{oc}' and short circuit currents 'I_{sc}' are also gets affected. It is found that the value V_{OC} and I_{SC} in more than two hot spotted solar cells get reduced when compared to the healthy panels. As shown in Fig. 2, the thermal images captured from the PV panels show the reduction of V_{oc} and I_{sc} due to the rise in the number of hotspots. The captured parameters are more helpful in developing a comparative PV fault detection system. The implementation of a comparative PV fault detection system is discussed in the next section.

TABLE II
SUMMARY OF THRESHOLD VALUES (MIN TO MAX) FOR ALL TYPES OF FAULTS

Health Status	Temp (^{0}C)		I_{rr} (W/m^2)		V_{OC} (V)		I_{SC} (A)		Z (Ω)		PPL (%)	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Healthy	33.3	44.2	365	900	9.9	10.8	0.5	0.95	10.61	20.22	0	0
One Hotspot	33.3	48.4	365	900	9.7	10.3	0.45	0.9	11.41	22.33	3.5	28.1
Two Hotspots	33.3	49.6	403	900	9.9	10.3	0.4	0.9	11.38	25.12	5.5	29.6
More Than Two Hotspots	33.3	52.1	403	900	9.9	10.4	0.35	0.9	11.57	28.6	4.1	43
Micro Crack	34.5	38.8	334	730	9.1	10.2	0.42	0.55	18.52	21.78	0.9	23.9

III. FAULT DETECTION USING ANN and SVM

The fault detection mechanism using ANN and SVM is elaborated in this section.

A. DETECTION USING ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is an information processing unit used for the classification and grouping of input data. The function of ANN is similar to the neural architecture of the brain. Similar to the brain, the neural network can perform functional operations like classifications and pattern recognition. Precisely, ANN is

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well noted to be more flexible and suitable for fault diagnostic system. Usually, ANN consists of three layers namely the input layer, hidden layer, and output layer. The hidden layer lies between the input and output layer which translates the nonlinear activation functions in between the nodes. The nodes are arranged in a sequential parallel layer interconnected by weighted connections. For fault identification, a single artificial neural network does not provide a precise solution. Hence, a three-layered feed-forward back propagation network is used in this work for fault identification. The architecture of this proposed system is shown in Fig. 3.

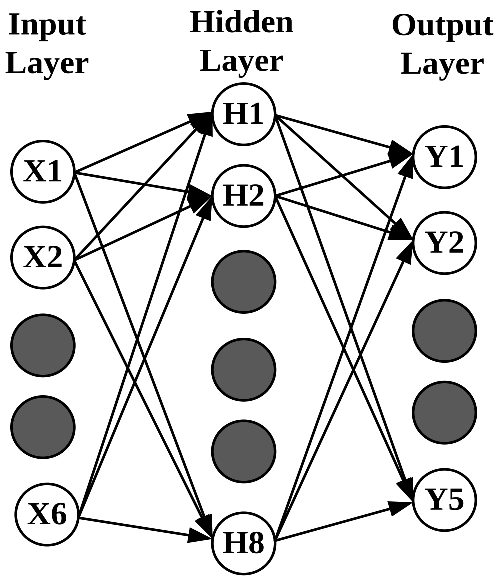

FIGURE 3. **Architecture of the Proposed Feed Forward Back Propagation Neural Network Method**

The feed-forward back propagation technique was introduced by Rumelhart in the year of 1986. If the back propagation algorithm is applied to the feed-forward multilayer neural network it is called Feed Forward Back Propagation Neural Network (FFBPNN). Since this neural network follows the error-correction rule, this network is also known as an error back propagation network. Here, the function signals will flow in the forward direction and error signals will flow in the backward direction. The parameters such as solar irradiation, panel temperature, V_{oc}, I_{sc}, Z, and PPL are obtained, and given as input (x1 to x6) to train the FFBPNN. The network is trained with all set of training pairs even in extreme conditions, and the input parameters are considered as target outputs by the FFBPNN.

To train the network, we must feed the network with output variables (y1 to y5) known as the target for a particular input variable. And the output variables here are our five classifications – healthy, one hotspot, two hotspots, more than two hotspots, and micro cracks. Once the network is trained, it can provide the desired output for any set of input patterns. In the initialization step, the weights are set randomly in the network. The weighted inputs can be computed using (3).

$$Y_{net} = \sum_{i=1}^{n} X_i * W_i + W_O \tag{3}$$

Where X_i is the input parameters, W_i is the weighted coefficient of each input parameters and W_0 is the bias. After initialization, the sums of the weighted input are transferred by an activation function as given in (4),

$$Y_{out} = f(y_{net}) = \frac{1}{1+ e^{-y_{net}}} \tag{4}$$

Where Y_{net} is the summation of weighted inputs, Y_{out} is the response of a system, f (Y_{net}) is the nonlinear activation function. The output obtained 'Y_{out}' from the above equation may not be the expected target due to random weights.
To adjust the weights, the error has to be calculated. The difference between target and actual output gives the error as expressed in (5).

$$E = \frac{1}{2}\sum_{i=1}^{k}(y_{obs} - y_{out})^2 \tag{5}$$

Where, Y_{obs} is the observed output value, and E is the error between the target value and actual output. The obtained error is used to change the weights so that, the error can be minimized. This training process is repeated until the target value is reached.

B. VALIDATION USING FEED FORWARD BACK PROPAGATION NEURAL NETWORK

The classification accuracy of various attributes using the FFBPNN fault detection system is given in Table III. According to the work reported in this paper, the input data is divided into a ratio of 70:30. Therefore, out of 100% data, 70% data are used for training and 30% data are utilized for testing. To evaluate the performance of the FFBPNN system, the data from various case studies are collected. The PV module is subjected to various fault conditions to produce different hotspots whereas; micro-cracks are created manually. Moreover, the panels are exposed to different temperature conditions and solar irradiations. The measured output parameters are given as the input to the FFBPNN detection system. An average accuracy of 87% is achieved while analyzing the individual condition's accuracies. Among various health statuses in the Table III, the healthy and more than two hotspot conditions show better accuracy. The remaining condition accuracy rate implies that there is a lesser confusion in classification. The implementation of the FFBPNN system is shown in Fig.4. The architecture of FFBPNN consists of six input layers, nine hidden layers, and five output layers. To achieve a better result, the hidden neurons, learning rate, and momentum rate must be taken into consideration. For processing the hidden layer, a quadratic activation function is chosen. Also, the number of neurons is randomly varied from 3 to 9 and finally, nine hidden neurons are fixed for better recognition. The

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maximum accuracy is obtained at a learning rate of 0.6 and a momentum rate of 0.4. The best validation performance of FFBPNN is depicted in Fig 5 in which, the best validation value of 0.0696 is reached at epoch 0.

TABLE III
CLASSIFICATION RESULTS USING FEED FORWARD BACK PROPAGATION NEURAL NETWORK METHOD

Health Status	Classification and Misclassification (%)					% Accuracy
	Healthy	One Hotspot	Two Hotspot	More than two Hotspot	Micro Crack	
Healthy	94.8	3.9	0.8	0.3	0.3	94.8
One Hotspot	14.9	80.9	2.3	1.4	0.6	80.9
Two Hotspots	2.9	5.7	88.0	2.9	0.6	88.0
More than two Hotspots	1.9	3.2	3.2	91.4	0.3	91.4
Micro crack	3.8	7.6	7.6	1.0	80.0	80.0
Average Accuracy= 87 %						

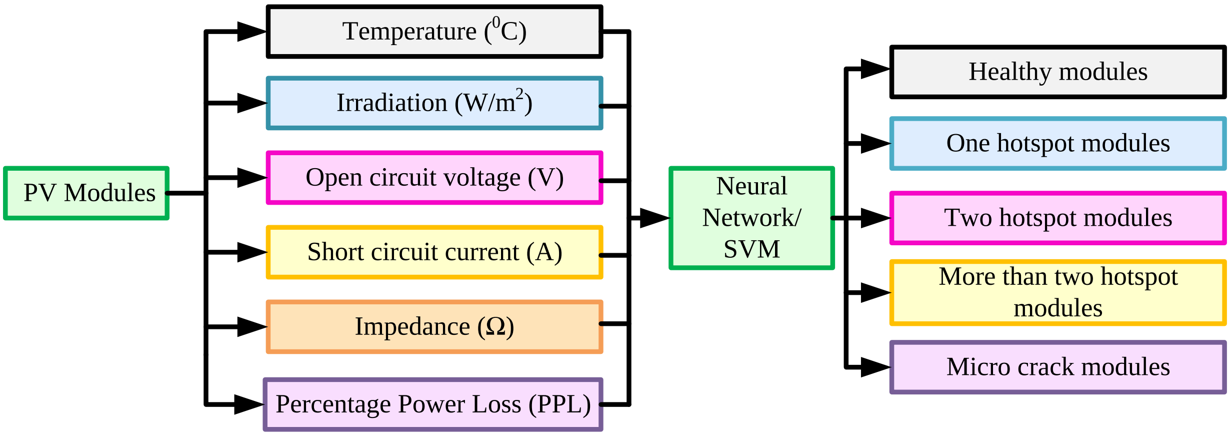

FIGURE 4. **Implementation of the Fault Detection System**

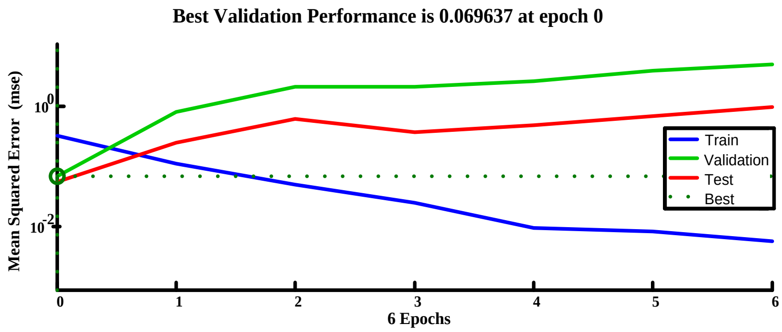

FIGURE 5. **Performance Validation Curve using FFBPNN**

C. DETECTION USING MULTI-CLASS SUPPORT VECTOR MACHINE SYSTEM

Support Vector Machine System is a supervised machine learning algorithm mostly applicable for classification problems. The Support Vector Machine (SVM) system is inherently a binary classifier normally applied for a two-class problem. But in the real case, to solve a problem with more than two classes, a multi-class SVM is required for classification. It is formed with multiple two-class classifiers.

The features obtained from the P-V and I-V characteristic curves are fed at each step of multi-class SVM. The input vector 'X' is mapped into high dimensional feature space 'Y' is given in the form

$$F_{SVM} = w^T \varphi(X) + b \tag{6}$$

Where, 'w' is a weight factor and 'b' is the bias function, these parameters are learned by using the training data set. The non-linear decision boundary for a training sample 'X' follows the condition.

$$w^T \varphi(X) + b \geq 1 - \xi \tag{7}$$

Where, ξ is the slack variable that provides a nonlinear constraint in SVM. The optimization problem in SVM uses the kernel function 'k'. This function maps the input space (X_i, Y_j) to the kernel space $\varphi(X_i), \varphi(Y_j)$ as:

$$k = \varphi(X_i)^T, \varphi(Y_j) \tag{8}$$

Here, Radial Basis Function (RBF) kernel is used for fault detection can be expressed as:

$$k(X_i, Y_j) = exp\left(-\frac{\|X_i - Y_j\|^2}{2\sigma^2}\right) \tag{9}$$

Where, $\|X_i - Y_j\|^2$ represents squared Euclidean distance between the two featured vectors, $\frac{1}{2\sigma^2} = \gamma$ Gamma function. Three parameters kernel 'k', Gamma 'γ' and regularization parameter 'c' are important to be considered in SVM implementation. Here RBF kernel function is used for the decision region. The 'γ' parameter decides the spread of the kernel to form the decision region. If 'γ' is low, the decision boundary curve also becomes low.

Therefore, the region is very broad. If 'γ' is high, the decision boundary curve is high, which forms a region of islands. Similarly, the 'c' parameter avoids the misclassification of data points. When 'c' is small, the bias 'b' will take a high value, and provides an accepted misclassification of data points. If 'c' is large, the bias 'b' value is low and the curve bends and avoids any misclassification of data points.

There are few constructing methods in a multi-class SVM, such as directed acyclic graph method, Binary Tree (BT) method, One against One and One against All. Among the various methods, the Binary tree method is proposed in this work to detect the fault in the PV modules. The highlights like computational efficiency and higher classification accuracy make the BT-SVM method superior to other methods. At each node of the binary tree, the decision is made to assign the input data into one of two groups. If the grouping is not done properly, it leads to performance degradation. In such a case, the overlapping of groups is needed to improve the performance. Self-Organizing Map (SOM) will convert a multi-class SVM into binary trees, and the decisions are taken by the SVM classifier. At each node, the input pattern is made to assign one of two groups. Here, the SOM provides the relationship among the input patterns. It is used to convert input space into visualized two-dimensional space. The standard SOM utilizes the simple Euclidian distance for mapping input space with kernel space. In the implementation of SVM with binary tree architecture for fault detection in the PV system, two-class SVM is implemented in four stages. In stage 1, SVM is activated to discriminate between healthy and unhealthy panels. The binary separable output is representing 1 as healthy and 0 to differentiate two hotspots as 1 and more than two hotspots as 0. Thus, all five categories of healthy and faulted PV modules present in a solar PV array are detected correctly. The working principle of this classifier is to discover a decision boundary with a maximum width that can classify two classes.

D. VALIDATION USING BINARY TREE – SUPPORT VECTOR MACHINE METHOD

To evaluate the performance using the BT-SVM method, in our case, we have five categories of output classes {1, 2, 3, 4, 5} and four stages of two-class classifiers. At SVM 1 stage, healthy {1} and unhealthy classes {2,3,4,5} is discriminated, At SVM 2 stage, micro-crack {5} and hot spot classes {2,3,4} are detected, In SVM stage 3, one hotspot {2} and multiple hot spot class {3,4} is identified. At the final SVM stage 4, two hotspots {3} and more than two hot spot classes {4} are classified as depicted in Fig 6. The classification accuracy of various attributes using the BT-SVM method is shown in Table IV. Though we have not applied any overlapping of groups, this method has achieved an average accuracy of 99.0%. Individual accuracies for all these mentioned conditions are also better ranging from 98.3% to 99.7%. Fig.7 (a) and (b) shows the input space and multi-class SVM. In a cluster of inputs available, the output five classes are classified at each SVM stage. Thus, multi-class SVM diagram implies the result as different faults and healthy modules are detected and classified wisely.

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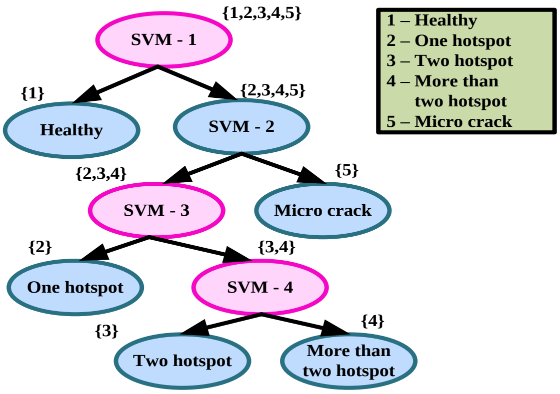

FIGURE 6. Binary Tree Architecture using SVM

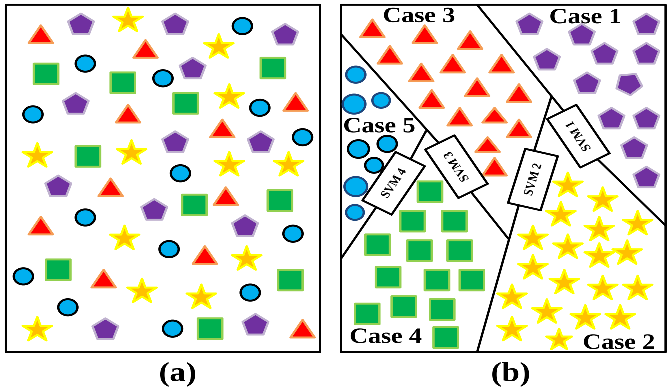

FIGURE 7. (a) Input Space (b) Multi-Class SVM

TABLE IV
CLASSIFICATION RESULTS USING BINARY TREE – SUPPORT VECTOR MACHINE METHOD

Health Status	Classification and Misclassification (%)					% Accuracy
	Healthy	One Hotspot	Two Hotspot	More than two Hotspot	Micro Crack	
Healthy	99.7	0.3	0.0	0.0	0.0	99.7
One Hotspot	0.9	98.3	0.6	0.3	0.0	98.3
Two Hotspot	0.3	0.9	98.9	0.0	0.0	98.9
More than two Hotspot	0.0	0.3	0.6	99.0	0.0	99.0
Micro Crack	1.0	0.0	0.0	0.0	99.0	99.0
Average accuracy= 99 %						

IV. RESULTS AND DISCUSSIONS

In this section, a few highlights of the proposed fault detection system are compared with existing literature (Dhimish and Badran, 2019) using fuzzy systems. Based on the input parameters considered, only three input parameters such as PPL, V_{OC}, and I_{SC} are considered in (Dhimish and Badran, 2019). But in the proposed method, six input parameters like I_{RR}, PPL, V_{oc}, I_{sc}, Z, and temperature are considered. If a greater number of input features are taken for processing, then the computation complexity increases. Still, the accuracy of the detection system gets improved. Furthermore, in the published work dealing with photovoltaic hotspot fault detection algorithm using fuzzy systems (Dhimish and Badran, 2019), only the problem due to the hotspot is concentrated. Different levels of hotspot such as one, two, and multiple hotspots are detected successfully. But in this proposed system, along with cases like various hotspots, healthy panels, micro-cracks are also detected. This capability of identifying broad categories will add a highlight to this detection system. A fuzzy-based detection approach is implemented in (Dhimish and Badran, 2019) which is an efficient method to achieve 96.7% accuracy whereas FFBPNN architecture produces an average accuracy of 87%. The reason behind the reduced accuracy is due to the application of additional parameter impedance at the input and micro crack in the output class. But on the other side, the SVM method has achieved an average accuracy of 99% which is a state-of-the-art approach that can perform well at any condition than the conventional approaches. SVM exhibit the advantages like assured optimality, convenience in implementation, applicable both in linear and -non-linear data. In detecting one hotspot, our SVM classifier and the literature mentioned fuzzy system shows the same accuracy rate whereas micro-cracks faults are additionally identified using SVM classifier with an accuracy of 99%. The comparison of results based on their accuracy using proposed techniques FFBPNN, SVM along with the existing fuzzy method is shown in Fig. 8.

From the accuracy comparison chart, it is evident that in healthy and micro cracks fault identification conventional fuzzy approach had not involved. In micro crack detection SVM method shows 90% accuracy whereas FFBPNN disclose only 80% accuracy. In hotspot detection, FFBPNN manifest least accuracy in all three classifications of hotspot as 80%, 88%, and 91% respectively in one, two and more than two hotspots. Although the conventional fuzzy approach appears closer values of accuracy percentage with the SVM method, SVM approach hits the slightly higher accuracy level in all the hotspots classification and detection. SVM does not have any over the fit problem when compared to ANN. Also, the RBF kernel provides more flexibility if

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there exist a non-linearity between the class labels and attributes. Besides, the faults can be identified at different temperatures. Fig. 9 and 10 shows the confusion matrix for the NN based classifier and SVM based classifier. The total numbers of data are 1505, in that 385 data is for healthy, 350 for one hotspot, 350 for two hot spots, 315 for more than two hotspots and 105 are micro crack. A confusion matrix is a table layout that confesses the conception of performance of an algorithm also known as an error matrix. Considering more than two hotspot classes in FFBPNN based classifier among the 315 data predicted only 288 data are classified under more than two hotspots and the remaining data are spitted in other classes. In our SVM based classifier, among the 315 predicted data, almost a major quantity of data are classified correctly mentioned as 312 in the confusion matrix which in turn increase the accuracy rate of the SVM classifier. Since most of the data are classified closer to accuracy in SVM classifiers compared to ANN classifiers, SVM classifiers express 99% average accuracy.

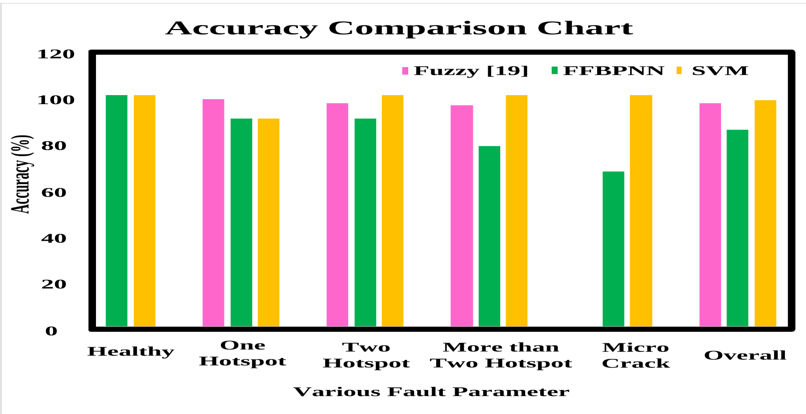

FIGURE 8. **Comparison of Accuracy with an existing method**

Confusion Matrix (Health Status /Classification)		Healthy	One Hot Spot	Two Hot Spot	More than 2 Hot Spot	Micro Crack	Accuracy 87 %
Healthy	385	365	15	3	1	1	94.8
One Hot Spot	350	52	283	8	5	2	80.9
Two Hot Spot	350	10	20	308	10	2	88.0
More than 2 Hot Spot	315	6	10	10	288	1	91.4
Micro Crack	105	4	8	8	1	84	80.0

FIGURE 9. **Classification results using FFBPNN based method**

Confusion Matrix (Health Status /Classification)		Healthy	One Hot Spot	Two Hot Spot	More than 2 Hot Spot	Micro Crack	Accuracy 99 %
Healthy	385	384	1	0	0	0	99.7
One Hot Spot	350	3	344	2	1	0	98.3
Two Hot Spot	350	1	3	346	0	0	98.9
More than 2 Hot Spot	315	0	1	2	312	0	99.0
Micro Crack	105	1	0	0	0	104	99.0

FIGURE 10. **Classification results using SVM based method**

V. CONCLUSIONS

Like all other power generation systems, solar panels are also prone to faults. These faults are required to be detected and classified expeditiously for the excellent operation of the PV system. Among the various faults in solar panels, failures such as hotspots and micro-cracks are inscribed in this work. Effect of hotspot on the performance of solar PV system based on the percentage of power loss, output impedance is analysed. A fault detecting model is developed with the help of MATLAB tool comprises of FFBPNN and Multi-SVM algorithms.

Among the two approaches implemented, the FFBPNN method has achieved an average accuracy of 87%, while the average accuracy of the SVM method is equal to 99%. The proposed SVM based technique yields 3.0% higher accuracy in comparison with the existing fuzzy-based techniques (Dhimish and Badran, 2019). The proposed technique also detects the micro-cracks with the highest accuracy of 99% whereas the existing fuzzy-based techniques (Dhimish and Badran, 2019) did not detect it. The advantage of this fault detection technique is that it can be performed at any environmental temperature and solar irradiations. While implementing in large scale solar power plant drone IR camera can be applied to reduce the labour work. In the future, it is aimed to implement the system to function under permanent partial shading conditions too.

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