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FAULT DIAGNOSIS IN GRID-CONNECTED PV SYSTEM USING MACHINE LEARNING TECHNIQUE

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***Abstract*—Photovoltaic (PV) systems are gaining significant attention due to accessibility, government incentives, and advances in PV modules. However, protection of PV systems against string-to-string (SS), string-to-ground (SG), open- circuit (OC) faults and partial shading is one of the main barriers to realizing economic and environmental-friendly PV systems. Such Abnormal conditions involving faults and partial shading lead to a reduction in the maximum available power from a photovoltaic (PV) array. Thus, it is necessary to detect faults in a PV array for improved system efficiency and reliability. The large fault current of PV systems can be detected by the available protective devices of PV systems such as fuses and residual current detectors. However, when the solar irradiation and/or fault mismatch is low and the fault resistance is high, the flowing fault current is not large enough to be detected by current-based protection devices. Thus, the Conventional protection devices fail to detect faults under cloudy and low irradiance conditions, leading to safety issues and fire hazards in the PV field. In this regard, a fault diagnosis scheme for PV systems is proposed which involves the derivation of discriminatory attributes of voltage-current information measured at the AC side using Wavelet transform based feature extraction technique and classification various faults in the PV system using Ensemble based machine learning technique.**

Keywords - Photovoltaic system, PV array fault, Fault Detection, Discrete wavelet transform, Ensemble of machine learning, Bagging tree classifier, etc.

I. INTRODUCTION

Solar energy has always been widely utilized due to its endless supply and benefits for the environment [1]. A photovoltaic (PV) system's operational faults have historically been one of the major factors affecting its power-generation efficiency under challenging and unstable climate conditions [2, 3]. However, faults on the direct current (DC) side of a PV system, such as open-circuit, short-circuit, degradation, and shading faults, are frequently challenging to avoid and can reduce the lifespan of the PV modules or even pose a serious safety risk.

There are several fault-detection techniques now in use, such as those based on thermal infrared detection, time domain reflectometry, AI algorithms, mathematical model analysis techniques, and more. The thermal infrared detection method uses an infrared scanner to measure the PV module surface temperature for abnormal heat brought on by faults. Nian et al.'s [6] design of image acquisition devices that can capture infrared images of PV modules makes use of the electroluminescence principles of semiconductors. The devices can identify faults in PV modules such as cracks, broken grids, black pieces, and fragmentation. Based on infrared image analysis, Peizhen and Shicheng [7] suggest a method that can automatically analyse and recognise the working status of the PV arrays.The thermal infrared detection technique, however, is primarily concerned with finding hot spot problems inside a PV array. The series PV module circuits of a PV array must first receive a pulse signal from the time domain reflectometry method, which then uses a comparison of the input pulse signal and the feedback output signal to determine the PV array's fault status. By using the change in response waveform to identify deterioration faults and pinpoint fault locations of the PV module in a PV array, Takashima et al. [8,9] use the time domain reflectometry approach. However, the PV system must be switched off while using the time domain reflectometry approach to find flaws, which will have a significant impact on the system's production.

This is helpful because it allows each panel to be tuned locally, which increases the amount of energy that can be harvested. This not only improves overall efficiency but also makes it possible to do individual measurements on solar panels. Because of these increased capabilities, there are now more opportunities available for monitoring the health of solar panels. This method, which is referred to as flaw detection, is a topic of ongoing study. The objective of defect detection is to locate damaged and deteriorated solar panels as quickly as is practically practicable. Solar panels will naturally degrade over time, and it is important to measure the pace at which this will happen.

II. LITERATURE REVIEW

In this section an overview of the previously proposed papers is given this will ultimately help to examine the disadvantages, advantages as well as the proposed work.

The k-nearest neighbours rule has been used in the classification and regression for string connected fault identification and diagnosis of PV systems [15]. This strategy is completely ready to recognize and characterize various sorts of issues continuously, for example, open circuit, line to line issues, halfway shading with/without sidestep diode faults and incomplete shading with rearranged sidestep diode deficiencies. Also, the proposed technique precisely follows the exhibition of PV frameworks at various insolation and temperature levels. In contrast with this technique, shading issues and deficiency location on the DC side of a framework associated PV framework are explored with exponentially weighted moving normal (EWMA) control diagram. The EWMA strategy had the option to distinguish the boundary changes between the shortcoming and ordinary conditions [2].

The instrument is to perceive the ordinary yield boundaries of PV framework, for example, most extreme force, current and voltage under various irradiance and cell temperature. The lingering, the contrast between the deliberate and anticipated yield from the single diode model, is taken as the fault pointer of PV frameworks. At that point, an EWMA outline is used to screen the non-corresponded residuals to recognize the sort of deficiency. For checking execution of PV frameworks, the factual methodology based univariate and multivariate exponentially weighted moving normal (EWMA) graphs approach is again used to recognize and analyze the deficiencies on DC side of PV framework [16]. A deviation number of electrical boundaries of PV frameworks under issue and typical conditions is resolved as the fault marker. Truth be told, the proposed multivariate EWMA can't recognize the deficiency types, except if the univariate EWMA plot is sent later to distinguish the short out, open-circuit and shading issues.

The observing capacity of shortcomings in PV frameworks is improved through the upgraded techniques for factual disappointment distinguishing proof [17]. The objective of the proposed technique is to diminish the support alert and missed recognizable proof rates by sending the multiscale-weighted summed up probability proportion test (MS-WGLRT) strategy.

The explanation behind this methodology is the multiscale nature may give better power to clamor and checking quality contrasted with the freely summed up probability proportion test strategy. Programmed recognition and determination of potential issues in network associated PV frameworks dependent on factual strategies thinking about atmosphere information and electrical boundaries are introduced as another option [18].

The calculation of fault identification based factual t-test is to look at the deliberate and perfect yield power, while the area of issue is resolved from the deliberate and perfect estimations of DC capacity to voltage proportion. This technique is successfully used to recognize various blames in PV board, PV string and MPPT controller. In the mean time, comparative factual techniques for t-tests and f-tests are utilized to examine the impact of splits on PV board electroluminescence estimations [19].

Ground fault and line-to-line fault are the most common causes of catastrophic array failures, while there are many other types of faults that can occur. A ground fault is an accidental low impedance current route between any current carrying conductor and ground, while a line-to-line fault is a fault path generated between any two places within the same or distinct strings in a PV array. Additionally, the phenomena of partial shade in PV arrays are very noteworthy. The output power of the PV array is temporarily impacted, however this is only transitory. There has been a lot of work done on PV array faults and how to detect and categorize them, but no research has been done on microgrids to help protection engineers distinguish between PV array faults and three phase symmetrical faults so that they can design relays with the proper control mechanism to prevent nuisance tripping.

In recent years, many strategies have been presented to secure PV integrated microgrids. Discrete wavelet transform and decision tree based approach [20], superimposed reactive energy calculation using Hilbert transform [21], time-frequency transform based differential scheme to obtain relay threshold setting [22], voltage magnitude and angle based classification scheme [23], fast recursive discrete fourier transform and fuzzy logic based decision making module for relay current setting [24]. No published research has attained that degree of sensitivity to include the aforesaid problems. Inspect PV array defects and disturbances that affect the microgrid protection mechanism.

Intelligent protection strategy efficacy is based on feature extraction and categorization. Feature extraction preserves contextual and discriminating information from original signals. Several time-domain, time-frequency domain, and transform domain feature extraction algorithms for microgrid protection have been presented. Discrete fourier

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transform (DFT) [25][26], discrete wavelet transform (DWT) [27], Hilbert-huang transform (HHT) [28], and S-transform [29].

III.GRID CONNECTED PV SYSTEM

In order for a photovoltaic (PV) system to ultimately result in the best possible trade-off in the context of a particular application, it must typically go through an optimization process that is directed by complex objective functions that embed a variety of criteria, some of which may be in conflict with one another. Methods of automatic control and signal processing are required during the exploitation time of PV systems. This is necessary in order to optimise the dynamic performance of the system, as well as its reactivity to the variability of the primary energy source, which is the light, and its robustness to any kind of disturbances. This paper will focus on a specific instance of one of these kinds of topologies.

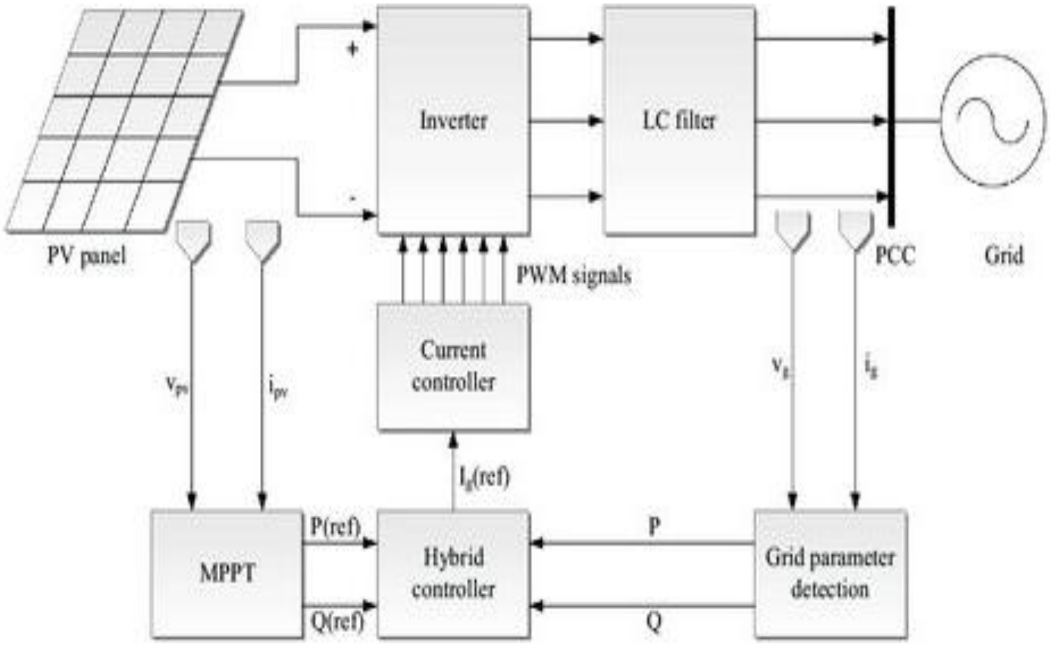

Figure 1: Typical Grid connected PV System block diagram.

A. MPPT Algorithms

There are a great variety of MPPT algorithms that have been created and put into practise [20, 21]. Some of them are really straightforward, and the necessary analogue control techniques may be carried out with little difficulty. The CV approach is one of the simplest ones. It keeps the voltage of the PV array at a specified limit, which corresponds to the MPP under a certain set of meteorological circumstances [21]. This will only provide an approximation of the real MPP while operating outside of the settings that were established. Short current pulse and open circuit voltage approaches are two further examples of approximate MPPT methods. The PV module is periodically shorted off by the SCP (or array). Calculating a current reference as a percentage of the short circuit current (usually 92% of the short circuit current) is possible [21].

The OCV does a similar task by opening the circuit of the array and establishing a voltage reference based on the open circuit voltage (often somewhere in the neighborhood of 76% of the open circuit voltage) [21]. Each of them has the drawback that it needs extra switches in order to either open or close the photovoltaic modules (or arrays). In addition, there will be no production of electricity throughout the time when the panel is in either the open or the short condition [21].

B. Fault Detection and Diagnosis

Novel categorization models have been developed in order to deal with fault detection and diagnosis as a result of recent research advancements in ANNs as well as the introduction of deep learning algorithms that use many layers that are both deep and complicated. [28] The vast majority of shallow learning models extract a small number of feature values from signals, which results in a decrease in the dimensionality of the initial signal. The continuous wavelet transform may be immediately categorized into normal and defective classes when convolution neural networks are used. A method like this one prevents the skipping of any critical error messages and ultimately leads to improved performance in problem identification and diagnosis. [29] In addition, in order to recognize erroneous signals based on vibration picture characteristics, it is possible to develop two-dimensional convolution neural networks by translating signals into image structures [30].

IV.PROPOSED METHODOLOGY

The grid connected PV system has been modeled and simulated as depicted in Fig 2. The PV array has been modeled as the distributed series-parallel combination of PV modules, with 3 parallel strings, each consisting of 4 modules in series, so that the impact of any failures in the array may be analysed as depicted in Fig 3. Each parallel string has a blocking diode linked in series with it so that back-feed current does not flow through it. Additionally, each module has a bypass diode connected in anti-parallel so that there are no hotspots when there is partial shading. There are now four distinct fault conditions that can occur inside a PV array. These faults include line-line faults within the same string, line-line faults across parallel strings, line-ground faults, and partial shading.

Algorithm Flowchart: In this section flowchart of the proposed fault diagnosis algorithm is discussed (Figure 4).

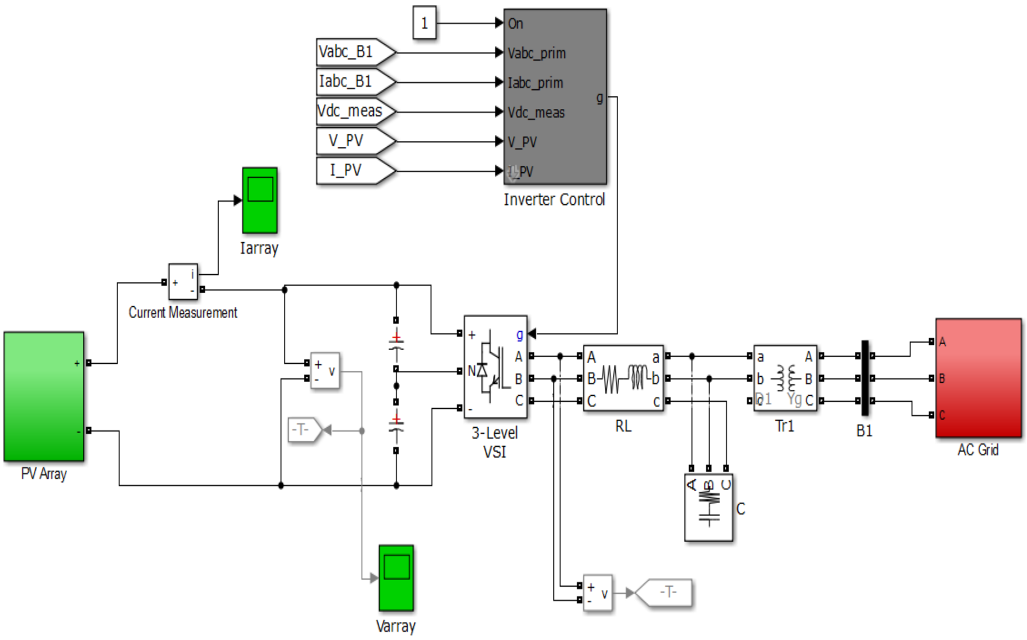

Figure 2: Simulation diagram of Grid connected PV System

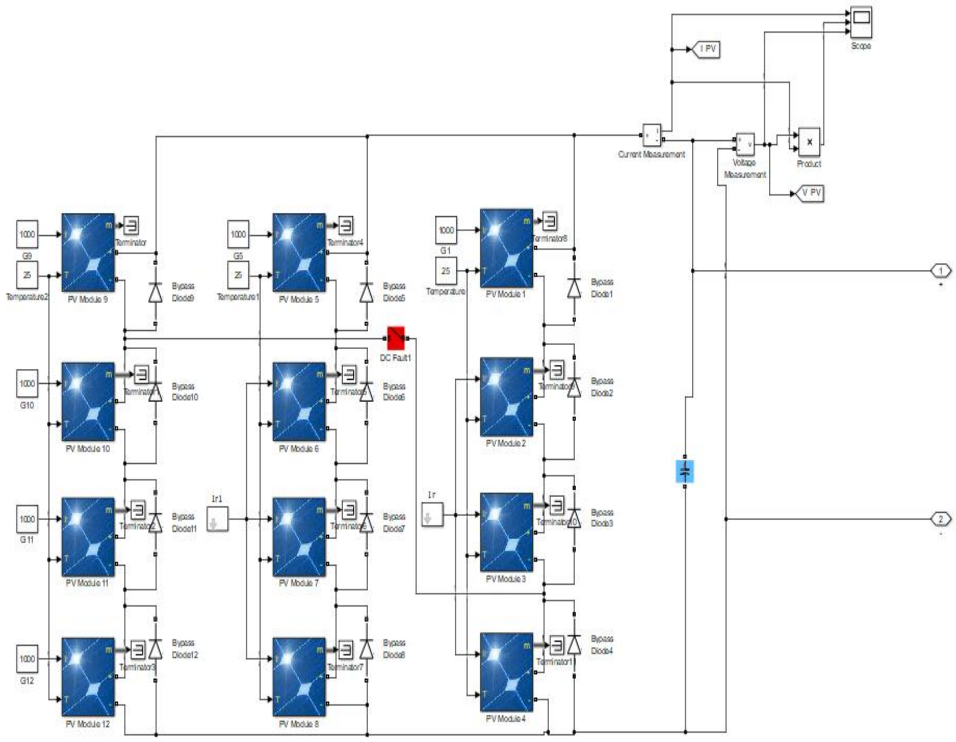

Figure 3: Series-parallel arrangement of PV array

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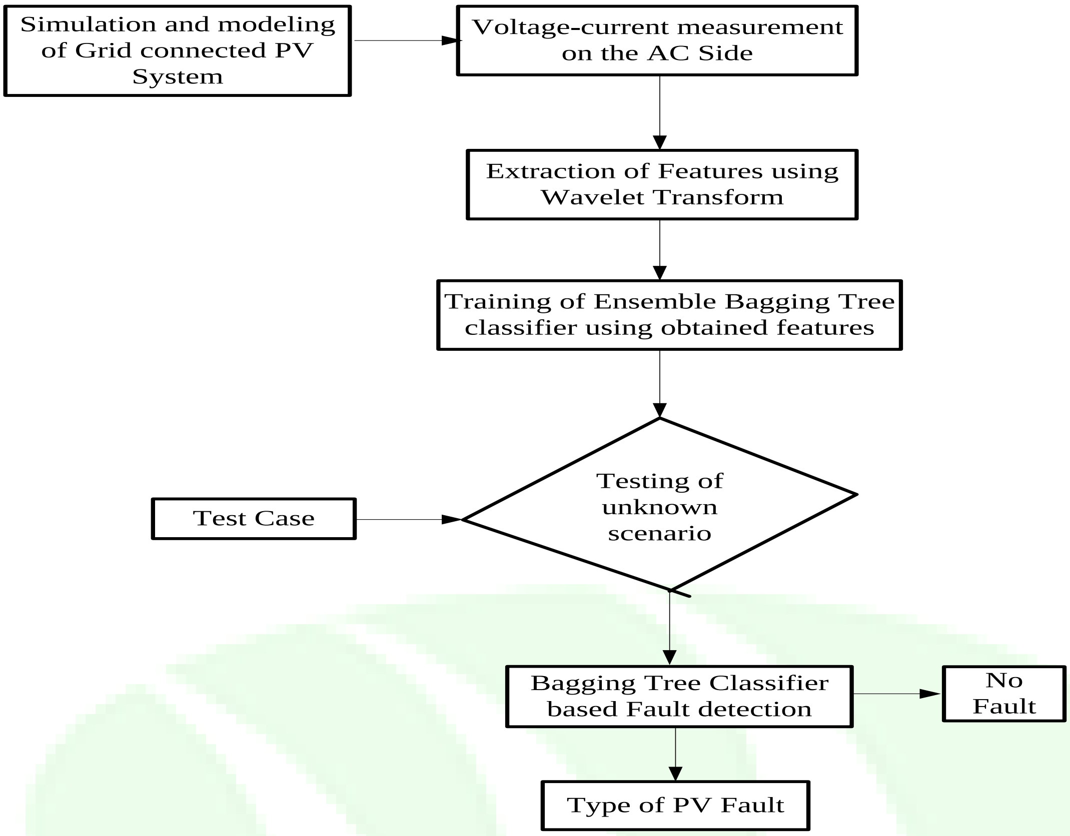

Figure 4: Flowchart of the proposed algorithm.

Working of proposed algorithm-

Step 1: The grid-connected PV system is modeled and simulated. The distributed PV array is simulated and the voltage and current signals are generated and recorded at the AC bus.

Step 2: The recorded voltage-current signals undergo feature extraction using Wavelet Transform.

Step 3: The features so obtained are utilized for training the Bagging tree based ensemble classifier.

Step 4: The trained network is further used to test an unknown scenario.

V. RESULT ANALYSIS

The distributed PV array module has been considered for simulating the various types of the faults such as pole-pole and pole-ground faults in the same or other strings in the PV module. The I-V and P-V characteristics of the array have been depicted in Figure 5. The characteristics at different irradiance levels are depicted in Figure 6. As observed, the Current and power levels goes down with reduction in the irradiance levels.

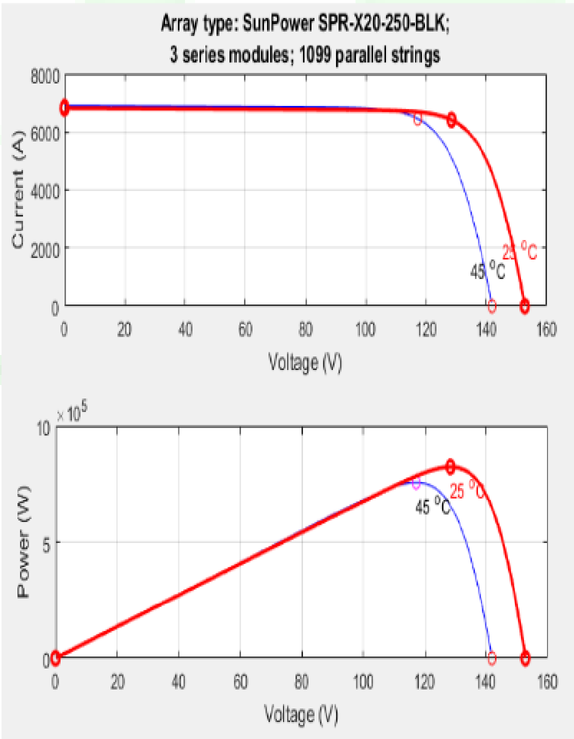

Figure 5: I-V and P-V characteristics of the array at different temperatures.

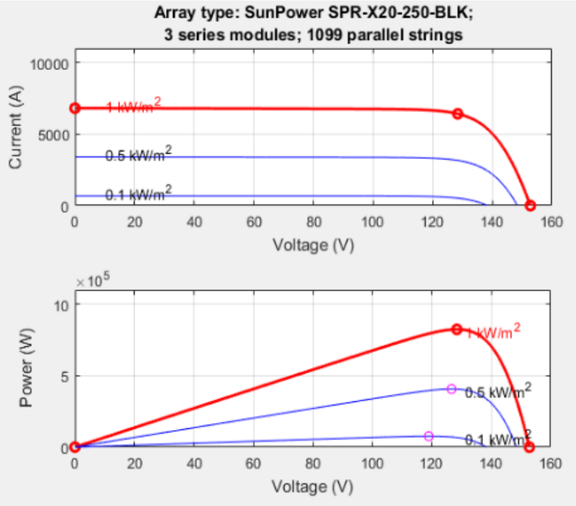

Figure 6: I-V and P-V characteristics of the array at different irradiance levels.

This section discusses how the proposed ensemble based scheme will perform against different fault situations caused by changes in different fault parameters. In order to examine failure detector/classifier performance a total of 550 test cases involving 500 fault and 50 no-fault cases has been considered. The findings of the analysis and comparative performance of proposed ensemble technique in terms of the classification accuracy, with SVM and DT based scheme shows clearly that the scheme proposed is efficient, reliable and immune to nonlinear loading conditions.

In the proposed study, an extensive data set is generated to train and test the data-mining model (using Bagging tree) for developing an accurate and robust classifier to perform the fault detection and classification task. The Bagging Tree based ensemble model is trained and tested for different combination of data sets, involving variation in fault parameters and other operating scenarios. For example in combination of (70–30) data set, 70% of data are considered for training purpose and 30% of data for testing purpose.

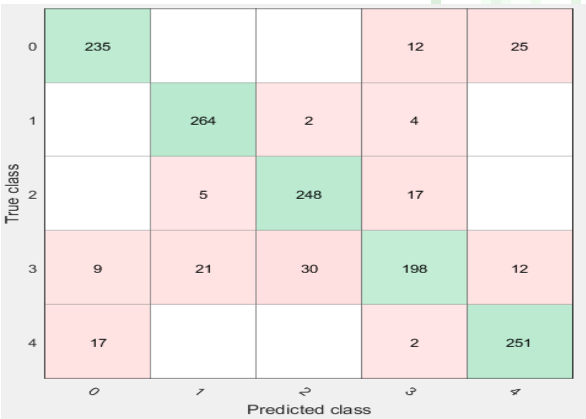

Figure 7: Confusion matrix showing the comparison between true and predicted class

Figure 8: Confusion matrix showing the variation between true positive and true negative rate

In order to show the robustness of proposed Bagging tree based classifier in performing the protection task, the Receiver Operating Characteristic (ROC) curve has been depicted in Fig. 7and Fig 8 which shows the ability in performing the intended tasks.

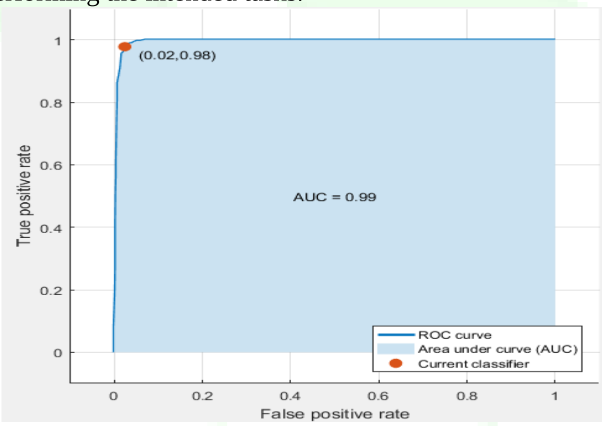

Figure 9: Receiver Operating Characteristic (ROC) curve of Bagged decision tree based classifier

In order to examine the performance of proposed Ensemble based classifier over other classifier, a comparative assessment has been carried out with Support Vector Machine (SVM) and Decision Tree (DT) classifiers in Table I. The high classification accuracy of 99.45% achieved by proposed Bagging Tree based Ensemble classifier over the SVM and DT based classifier clearly confirms the effectiveness of proposed approach in performing the PV array fault detection and classification task.

Table I: Comparison of proposed Bagging Tree based classifier with other individual classifiers

Type of classifier	**Number of test cases**	**Correctly predicted Test cases**	**Classification Accuracy**

Baaging Tree Classifier	550	547	99.45%
Support Vector Machine (SVM)	550	493	89.63%
Decision Tree (DT)	550	509	92.54%

VI. CONCLUSION

Accessibility, government incentives, and breakthroughs in PV modules are boosting PV's popularity. Protection of PV systems against string-to-string (SS), string-to-ground (SG), open-circuit (OC), and partial shadowing is a barrier to economic and environmentally favourable PV systems. Such Abnormal situations like faults and partial shadowing reduce photovoltaic (PV) array power. To increase system efficiency and reliability, detect PV array issues. Fuse and residual current detectors may detect significant PV fault currents. Low sun irradiation and/or fault mismatch and high fault resistance prevent current-based protection devices from detecting fault current. Conventional protection devices fail to identify defects in overcast and low-irradiance circumstances, posing safety and fire dangers in the PV field. In this context, a fault detection approach for PV systems has been presented, which comprises deriving discriminating features of AC voltage-current information using Wavelet transform-based feature extraction and classifying various PV system problems using Bagging Tree based Ensemble-based machine learning. The performance comparison of Proposed Bagging Tree based classifier with SVM and DT based classifiers clearly depicts its outperforming response in performing the intended tasks of fault detection and classification in PV array.

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