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OPTIMIZED MULTITASK MULTI ATTENTION RESIDUAL SHRINKAGE CONVOLUTIONAL NEURAL NETWORK FOR FAULT DETECTION IN SOLAR PHOTOVOLTAIC SYSTEMS

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Abstract

The world's population is growing and technological improvements are causing an excess of energy use over supply. It is imperative to move closer to a dependable, affordable, and sustainable renewable energy source in order to meet future energy demands.This article offers an interesting concept for research instructors to comprehendaneffect of faults on solar panels and what research have been completed by various approaches, with a machine learning approach to discover glitches. The investigation also sheds light on how to improve solar panel power efficiency and perform defect correction.In this research work, Optimized Multitask Multi attention Residual Shrinkage Convolutional Neural Networkfor Fault Detection in Solar Photovoltaic Systems (MMRSCNN-FD-SPV)is proposed.Initially, the input data is collected from Fault Detection Dataset in Photovoltaic Farms. Then, the collected data is preprocessed using Generalized Multi-kernel Maximum Correntropy Kalman Filter (GMMCKF) used to clean data. Afterwards, pre-processed data is given for Quantum Conditional Generative Adversarial Network (QCGAN) for effectively detects the

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various possible burdens that occur in photovoltaicboards.Then, Multitask Multi attention Residual Shrinkage Convolutional Neural Network (MMRSCNN) is used to identifying the fault analysis of photovoltaic panels as Fault-free system (FFS), string fault (SF), string to ground fault (SGF) and string to string fault (SSF). In general, MMRSCNN does not disclose any acceptance of optimization methods for computing the ideal parameters for assuring exact identification of fault diagnosis of photovoltaic panels. Therefore in this work,Chameleon Swarm Optimization Algorithm (CSOA) [26] suggested to optimize weight parameters of MMRSCNN. The suggestedtechnique is implemented and analyzed with help of performance measures such as Exactness, precision, f1-score, sensitivity, specificity, Error rate and Calculation time.Performance of MMRSCNN-FD-SPV approach attains 28.75%, 26.89% and 32.57% higher accuracy; 31.87%, 24.57% and 32.94% specificity and 25.43%, 19.64% and 31.40% higher sensitivity when analyzed through existing techniques like Then performance of MMRSCNN-FD-SPV proposed technique is associated with existing method like an actualestimation on fault discovery in solar panels (EE-FD-SP) [16] and Line-line fault detection and classification for photovoltaic systems using ensemble learning model based on IV characteristics (LLF-CPV-EL) [17],a novel convolutional neural network-based method for fault sorting in photovoltaic arrays (CNN-FC-PA) respectively

Keywords: *Chameleon Swarm Algorithm, Fault Detection, Generalized Multi-kernel Maximum Correntropy Kalman Filter, Multitask Multi attention Residual Shrinkage Convolutional Neural Network and solar Photovoltaic Systems and*

1. Introduction

The last ten years have seen a rapid development in photovoltaic (PV) systems worldwide, and the market is expanding dramatically [1]. But improvements in defect detection or system monitoring, particularly in PV systems with below 25 kW of output power, have not kept pace with this progress. In the realm of solar energy, reliability analysis has been done after accounting for variations in operational and environmental circumstances. One essential factor that makes the solar energy process possible is sun irradiation [2,3]. Predicting solar panel failures requires some scepticism based on surroundings such temperature, relative humidity, number of clouds, dust, and irradiance. Faults in the solar panels additionally cause the plant's services to be less frequent and efficient, but they may also lead to unusual situations [4]. Defect detection may therefore result in power outages if defects in solar arrays are not properly addressed, and occasionally accidents may affect the entire system as a whole. In grid-connected solar systems, many tactics can be applied to offer promising failure detection [5,6]. Some of them employ meteorological and astronomical data to identify GCPV plant malfunctions. Nevertheless, none of the meteorological information (irradiance, panel temperature, shade quantity) is needed for other PV defect identification methods, as Taka-capacitance Shima's studies [7]. Additionally, sensor diagnosis signals are used to alert grid-connected PV (GCPV) plants to possible flaws in their PV module. When a PV system's fault detection algorithm is employed, it can offer comprehensive details on current generation under typical operating conditions. When a defect is fixed, power losses are

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decreased and the solar power system performs better [8-10]. PV arrays can anticipate the highest possible coordinates of current, voltage, and power using observed temperatures and irradiances when one adopts the one-diode method, which requires calibration due to restricted calibration variables [11]. By estimating their beginning ranges, real-time watching and error monitoring of solar systems can also be used to detect faults. Thus, this method allows for the timely tracking of the solar system when the minimum and maximum thresholds for a given problem are found [12]. Due to environmental factors, irreversible device damage, and human mistake, PV arrays might encounter a variety of unexpected issues. One of the main catastrophic failures that impairs solar power and, in the nastiest scenario, causes a fire tragedy is the Line-Line (LL) fault [13]. Climatic influences, permanent device damage, and human error can all result in a range of unforeseen challenges for PV arrays. The Line-Line (LL) error is the primary catastrophic failures that reduces solar power and, in the worst case, results in a fire disaster [14]. A key component of PV system security and performance is PV detection. Without diagnosing PV flaws, the ambiguous fault results in power loss and may also pose a risk of fire and safety issues [15]. The shadow cast by trees, chimneys, or buildings, which affect the system's overall output, are additional elements that lower PV system effectiveness [16].The remote monitoring system evaluates the PV array's primary attributes, including output voltage, current, and power, by analysing the data that has been observed [17]. By relating the calculated data and analysing PV system specification, the fault can be located. In addition to being the cause of the plants less frequently occurring and inefficient operations, solar panel malfunctions may also result in unusual situations [18].Therefore, failure to detect faults in solar arrays may result in power outages, and when faults in solar arrays are present, the system as a whole may have accidents. For grid-connected solar systems, there are a number of promising failure detection techniques that can be applied [19]. Focusing on fault detection in grid-connected solar systems aims to ensure the stability, efficiency, and security of solar power plants, supporting the transition to a more sustainable and resilient energy infrastructure in the process. These are what spur us on to carry out this research [20].

The main contribution of this work,

- The usage of the Fault Detection Dataset in Photovoltaic Farms provides a solid basis of real-world data.
- Using the GMMCKF for pre-processing is an advanced technique to improve and clean the data, guaranteeing that any analysis that follows will be based on factual information.
- A new approach for fault detection in photovoltaic panels is QCGAN, which makes use of quantum computing concepts.
- Since MMRSCNN is used for fault diagnosis, it can identify many fault kinds. The intricacy of defect diagnosis jobs in PV systems is suited for this neural network architecture.
- MMRSCNN can identify a wide variety of fault types because it is utilized for fault diagnosis. This neural network architecture is appropriate for the complex defect diagnosis tasks in PV systems.

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The remainder of paper is arranged in given below. Literature review presented in section 2, materials and procedures employed article discussed section 3, result then discussion described section 4, conclusion presented section 5.

2. Literature Review

Numerous research works existing in the literature to identifyFault diagnosis by deep learning; a few current works are labeled below.

In 2021, Dhanraj, et.al, [21] hasoffered an effective estimation on errorfinding in solar boards. Photovoltaic (PV) panels are used field of solar power creation to convert solar radiation into electricity. As soon as feasible, these flaws should be found and fixed to ensure that the endurance, durability, and efficiency of PV panels are not jeopardized.This paper is divided into five main sections: (i) the different types of PV panel faults that can arise; (ii) online/remote PV panel supervision; (iii) the part of machine learning methods in PV panel erroranalysis; (iv) the different types of sensors used for dissimilar PV panel fault findings; and (v) the advantages of PV panel fault recognition. It provides higher exactness and lesser accuracy.

In 2020, Eskandari, et.al, [22] hasproposed Line-line errorfinding and classification for photovoltaic systems using ensemble learning methoddepend on IV features. In this research suggests intelligent fault analysis technique depend on ensemble learning method and Current-Voltage (I-V) features. First, examining the I-V characteristics and during normal operation. Secondly, a feature choiceprocedure has used to select the optimum characteristics for each learning procedure.Third, in order to attain better diagnostic performance; an ensemble learning method based on the probabilistic method is created by combining multiple learning algorithms.It provides higher f1-score and lower accuracy.

In 2020, Aziz, et.al, [23] has presented a novel convolutional neural network-based approach for fault organization in photovoltaic collections. The suggested method is thoroughly quantitatively evaluated and contrasted with earlier approaches to PV array defect classification, including both deep learning and standard machine learning based approaches.Unlike recent work, have included MPPT in analysis and have taken into consideration five distinct incorrect instances. First thorough and significant comparative assessment of fault identificationand method to be compared to earlier techniques.It offershigher precision and lesserF1-score.

In 2021, Alves, et.al, [24] has presented automatic fault organization in photovoltaic unitsby Convolutional Neural Networks (CNN). This study aims to examine the influence of data augmentation approaches on the act of suggested convolutional neural networks (CNNs) for the classification of anomalies in PV units using thermo graphicpictures in an unbalanced dataset. The CNNs can categorize anomalies into up to eleven different classes.When developing an automated tool to categorize a wide range of problems in PV plants; matrices of confusion are used to examine the high within- and among-class difference in distinct classes.It provides higher sensitivity and lower accuracy.

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In 2023, Mustafa, et.al, [25] have suggested Fault identification for photovoltaic systems using a multi-output deep learning (DL)method. In this work, three multi-output DL algorithms-convolutional neural networks (CNN), bi-directional long short-term memory (Bi-LSTM) , and long short-term memory (LSTM) networks-are used to identify, categorize, and find SS, SG, and OC errors.When related to prior techniques in the literature, the suggested method lowers a number of sensors required per string. Using an uncoupled modellingtechnique, it also permits greater scalability and creation of multi-label data collection.It provides higher specificity and lower precision.

In 2021, Badr, et.al, [26] have presented Fault recognition of photovoltaic array depend on machine learning classifiers. This work attempts to express an optimal machine learning (ML) structure of automatic diagnosis and detection procedure for common PV array errors under various climate data collection, fault impedances, then shading scenarios. These include permanent and temporary (Shading) faults.Three different ML classifiers are compared in order to determine the best-fit ML structure: Decision Tree (DT) depends various splitting criteria, K-Nearest Neighbors (KNN) depends various distance and weighting function metrics, then Support Vector machine. It provides higher precision and highererror rate.

In 2021, Hajji, et.al, [27] have presented Multivariate feature removal based supervised ML for errorfinding and diagnosis in photovoltaic systems. In this work is to create a better failure detection method for PV systems. The two primary steps of the typical FDD technique are fault sorting and feature removal and assortment. For the purpose of monitoring multivariate statistical systems, multivariate feature withdrawal and choice is crucial.The principal component analysis (PCA) method utilized in this suggested FDD methodology to remove and pick the most pertinent multivariate attributes, and supervised machine learning (SML) classification tools performed to identify problems.It offers higher sensibility and lower f1-score.

3. Proposed Method

In this proposed methodology, (Optimized Multitask Multi attention Residual Shrinkage Convolutional Neural Networkfor Fault Finding in Solar Photovoltaic Systems) MMRSCNN-FD-SPV discussed for ErrorFinding in Solar Photovoltaic Systems. This process consists of five steps: Data acquisition, Pre-processing, detection, classification and optimization. This model composed four of fault diagnosis of photovoltaicpanelsclassification, such as Fault-free system, string fault, string to ground fault and string to string error. The model endures initial data gathering byFault Detection Dataset, undergo pre-processing to prepare them for further analysis. Next in the final step involves employing MMRSCNN for identifying the presence, location, and classifications of a fault diagnosis of photovoltaic panels and then it is sent for further processing.The Chameleon Swarm Optimization Algorithm (CSOA) method introduced for training the MMRSCNN. Block diagram of MMRSCNN-FD-SPV is represented by Figure 1.

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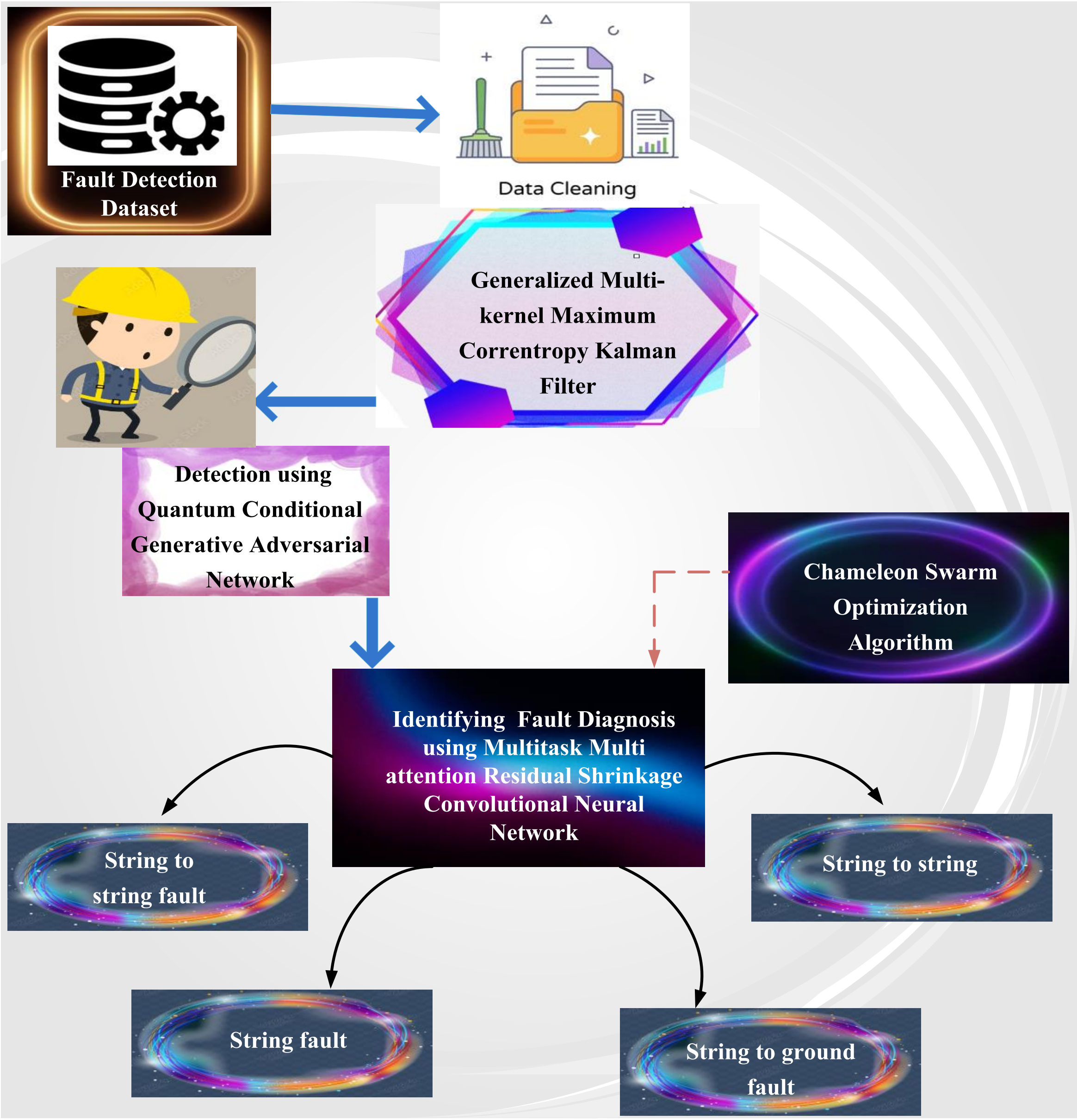

Figure1: Proposed MMRSCNN-FD-SPV for photovoltaicpanelsclassification.

3.1 Data acquisition

Hereinformation is gathered as ofFault Detection Dataset[28] in Photovoltaic Farms. Training and testing data collection of PV fault conditions was created using simulated 250-kW PV power capacity. In Appendix A, the PV farm and its imitation are covered more detail.Datasets for testing and training were created. There were 600 cases in the training dataset, and each one had 30 characteristics along with a column for classifications or categories. All measurements in the training dataset were made among 0.2 and 0.4 seconds after the problem ensued. There were fifty cases in the testing dataset. Measurements were made among 0.1 and 0.3 seconds, during which faults happenedamong 0.2 and 0.3 seconds, and transient time fell among 0.1 and 0.2 seconds.

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3.2 Pre-processing usingGeneralized Multi-kernel Maximum Correntropy Kalman Filter

In this step, data pre-processing using Generalized Multi-kernel Maximum Correntropy Kalman Filter (GMMCKF) [29] is discussed for clean data in the Fault Detection Dataset. GMMCKFmakes use of several kernels to capture various facets of the behavior of the data. Every kernel concentrates on particular traits or trends in the data. One kernel, for example, may be susceptible to low-frequency trends. This flexibility is essential for efficiently cleaning data in the face of fluctuating noise levels or shifting environmental circumstances. It is the best option for clean the dataFault Detection that may have varying qualities and variances in the input information. Applications involving data processing may benefit from this measuresand increased performance. To create a measure of similarity that is more resilient to outliers, initialize the Kalman Filter using the system dynamics model, it is shown in equation (1)

$$y_{l+1} = By_l + w_l$$

(1)

Where, $y_l \in \Re^m$ indicates the states, w_l represents the Gaussian noises with $w_l \sim M(0, R_l)$, B represents the measurement, R_l have $R_l > 0$, B assuming to be controlled. The initial state $y0 \sim M(0,0)$ indicates uncorrelated with w_l for $l > 0$. Define the measurement parameter set up to time step l as $y_l := \{z_1, z_2, ..., z_l\}$. Based on noise distribution, KF is ineffective as an estimator. In some cases, nominal noises may follow distinct patterns. All these factors reduce an estimation accuracy of the Kalman Filter is given in equation (2),

$$\hat{y}_i^- = B\,\hat{y}_{l-1}^+$$

(2)

Where, $\hat{y}_i^-$ represents the input dataof y_l, $\hat{y}_{l-1}^+$ represents the posterior estimate of y_l, Q_l^- represents the priori estimation of fault invariance at time step l, Q_l^+ signifies the represents the priori assessment of error covariance at time step l. The Correntropy is initially well-defined as a measure of local comparison among two random variables with joint supply is given in equation (3),

$$l(y,z) = \exp\left(-\frac{f^2}{2\gamma^2}\right)$$

(3)

Where, $f = y + z$ represents the bandwidth, γ signifies the kernel bandwidth, $y(l)$ and $z(l)$ are available in M samples, f^2 indicates the norm based data function, y indicates the first taken random vector, z represents the second taken random vector, $y, z \in \Re J$ indicates

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$j-th$ component of Y is Y_j and Z is Z_j. The covariance matrices and state estimate are updated using the formula (4)

$$\bar{l}_{\delta,\lambda_j}\left(y_j, z_j\right)=\lambda_j^{\delta} \exp\left(-\left|f_j/\lambda_j\right|^{\delta}\right)$$

(4)

Where, y_j indicates the realizations of Y_j, z_j indicates the realizations of Z_j, $f_j = y_j - z_j$ represents the realization error, λ_j specifies the $j-th$ bandwidth for Z_j, δ specifies the $j-th$ bandwidth for Y_j. In an actual scenario, the joint distribution $G_{Y_j Z_j}\left(y_j, z_j\right)$ is unavailable and M samples can be gained. The data is clean in equation (5),

$$D_{\delta.\lambda_J}\left(Y_j, Z_j\right)=\frac{1}{M}\sum_{l=1}^{M} H_{\delta,\lambda_j}\left(y_j(l), z_j(l)\right)$$

(5)

Where, $D_{\delta.\lambda_J}\left(Y_j, Z_j\right)$ signifies the Correntropy for Y_j, Z_j, Y_j under δ and Z_j under λ_j, $y_j(l)$ is the $l-th$ sample of casual variable $Y_j, z_j(l)$ is the $l-th$ sample of casual variable Z_j, δ parameter indicates clean the data , λ signifies the various bandwidth in H_{δ,λ_j}. Finally, data is cleaned by using the GMMCKF. Then the initial-processed image is suckled to classification phase.

3.3 Detection usingQuantum Conditional Generative Adversarial Network (QCGAN)

In this section Quantum Conditional Generative Adversarial Network (QCGAN) [30] is discussed for effectively detects the manylikely faults that happen in photovoltaicboards.QCGANare able to identify patterns in data. Because PV panels are reliant on their surroundings, it is possible to forecast their production, problems, and efficiency.Algorithms for QCGANcan find patterns in data. PV panels can have their production, issues, and efficiency predicted because they are dependent on their environment.In this method, machine learning algorithms are utilized to analyze the equipment's operation and predict when repairs are needed. In this method, technicians can avoid expensive breakdowns and unnecessary maintenance.In contrast to traditional quantum generators, the QCGAN necessitates the incorporation of conditional information in the form of probability distributions and several input data types. The implementation of conditional information encoding is shown in equation (6).

$$|x\rangle = q_1 |00\rangle + q_2 |01\rangle + q_3 |10\rangle + q_4 |11\rangle \quad (6)$$

Where, type of aberrant data corresponds to each basis state of $q_1, q_2 and\ q_3$ and the chancesupply of that kind of irregular heartbeat is represented by x.By adjusting the probability values, one can regulate the kind of target heart rate that the generator produces. The feature vectors from the dataset can be encoded into quantum states using quantum

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circuits. A group of qubits can be used to represent each feature. In the event that nn features exist, for instance, the quantum state can be expressed as following equation(7)

$$|a\rangle = \overset{M}{\underset{i=1}{\otimes}} G_X(a_i)|0\rangle \tag{7}$$

Where, a indicates the the quantum state encoding the i feature. Random sampling of noise: In the latent space $X \in R$, the noise path is randomly tested such that each noise point. Using the G_X gate, the quantum clean data vector $\overset{M}{\underset{i=1}{\otimes}}$. The QCGAN's generator is a quantum circuit that generates a generated quantum state, from a random quantum state X , as input. This quantum state is an artificial sample designed to resemble the distribution of data from PV panels without faults.The random data sampling is given in equation (8)

$$|\psi^f(a)\rangle = D^f(\vec{\theta}^f)|a\rangle \tag{8}$$

Where, ψ^f denotes the random data sampling. The clean datapath is randomly tested in the hidden space $X \in R$ so that every data point satisfies $X \in [0,2k]$. Next, extract the quantum noise vector by the RYgate: Another type of quantum circuit is the discriminator, which receives a quantum state q^f as input and outputs a probabilityis given in equation (9)

$$k^f = [q^f(0), q^f(1), ..., q^f(2^{M-M_A} - 1) \tag{9}$$

Here, k^f that indicates the input is a generated sample, $q^f(0), q^f(1), ..., q^f$ represents the quantum gate sequence. After that, each sub-generator 2^{M-M_A} measurement result M establishes a quantification of the difference among the created information distribution and data distribution using the quantum loss function. The photovoltaicpanel's detection is done by equation (10)

$$\vec{\theta}' = \vec{\theta} + \eta_D \frac{\partial W(D)}{\partial \vec{\theta}} \tag{10}$$

Similarly, the generator's gradient $\partial W(D)$ can be ascertained by applying the parameter shift rule. The quantum discriminator's $\vec{\theta}'$ parameter update is carried out in this step. Use the generator to create artificial fault-free samples η_D once the QCGAN has been trained. To find errors, compare these produced samples with samples of actual data using quantum similarity metrics. By using QCGANeffectively detects the numerous possible faults that ensue in photovoltaicboards. Then the data are given to classification section.

3.4Identification using Multitask Multi-attention Residual Shrinkage Convolutional Neural Network

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This section discusses theMultitask Multi attention Residual Shrinkage Convolutional Neural Network (MARSCN) [31] is used to identifying the errorjudgment of photovoltaic panels as FFS, SE, SGE and SSE. MARSCN specifically utilizes the number of free parameters, which are mostly established by the distance margin utilized to distinguish between various places.The MARSCN approach needs electrical and environmental data while the PV panel is operating in order to get the desired results. MARSCN techniques work on the basic tenet that a large solar system requires exposure of the entire string to a wide range of temperatures and irradiance. When a mixture of flaws and thestring's defective module locations are combined, the outcome. There might be string current seen.A PV system's ability to identify faults successfully is entirely dependent on the many approaches that different researchers have used. Primary reasons depict the shrinkage operationwhich aims to discover subsets with the fewest and it is given in equation (11)

$$F(D_m) = \frac{1}{t}\sum_{i=1}^{t} D_m(C) \tag{11}$$

Where m remains the vector's length. The identical procedure is then carried out using D_m , the weighted vertex cover information, F shrinkage operation. The rectified linear unit is taken by the first layer, and the sigmoid function is taken by the second layer C as inactive part. The captured competing group's probabilities are following equation (12),

$$G_n = Fuzzy\left(P_2^{S^{n\times\left(\frac{n}{s}\right)}} \operatorname{Re}lu\left(P_1^{S^{\left(\frac{n}{s}\right)\times n}} N(V_n) + A_1 \right) + A_2 \right) \tag{12}$$

Where V_n denotes captured channel weight, A instantaneous power produced by the PV system, A_2 denotes dimensionality increasing data, $N(V_n)$ signifies dimension reduction ratio, $\operatorname{Re}lu$ activation processes work together to train the latter to have specialized activations. G_n denotessolar panels, $P_2^{S^{n\times\left(\frac{n}{s}\right)}}$ meaning one-eighth of feature variable in preceding layer corresponds to the quantity of data in the initial dense layer. Lastly, to raise the distance of crucial information channels, multiply learned weights by corresponding channels. The methods canconcentration on different areas of the input data according to the task at hand, which improves its capacity to identify certain errors. Formula is shown in equation (13),

$$V_n^{DB} = V_n \otimes R_n \tag{13}$$

Where V denotes altered feature vector within the channel, $\otimes$ signifies multiplication of elements, R denotes the current layer, DB represents the current signal, number of network layer increases is denoted by n . The network primarily considers time information of the class sequence when calculating time domain feature distance. The activation functions and convolution layers capture the weights between different data types. The fault diagnosis is identifying as Fault-free system, string fault by calculating the equation (14).

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$$G^* = Sigmoid\left(K^{S^{1\times h}} H_p + J\right) \tag{14}$$

Where G^* the detect specific faults and K denotes dimensionality-reduction path time $1 \times h$ is the deep layer, J is the size of the features, predicted fault type probabilities denotes H_p. Finally, learnt time $Sigmoid$ domain variance multiplied by location to enhance the path planning process. The fault diagnosis is identifying as string to ground fault and string to string error by calculating the equation (15).

$$\xi_U = \beta_m M^*(Q_w) \tag{15}$$

Where ξ_U denotes the data mining of function, β_m is the main value of data function, M^* is the multiple value, (Q_w) is the defective modules in the string. The results of this equation demonstrate that identified the SGE and SSE. Finally MMRSCNN model classifies fault diagnosis of photovoltaic panels such as FFS, SF, SGF and SSF. Utilizing Chameleon Swarm Optimization AlgorithmCSOAemployed to enhance MMRSCNN. The CSOAused to adjust the MMRSCNNweight and bias parameter.

3.5 Optimization using Chameleon Swarm Optimization Algorithm

The proposedChameleon Swarm Optimization Procedure(CSOA) [32] is utilized to enhance weights parameters G_n *and* ξ_U of proposed MRSCNN. With a diverse spectrum of species, chameleons are unique, highly specialized clade that is well-known for capacity to change data to fit in with environment. They live in lowlands, rainforests, deserts, semi-desert areas, even mountains, among other diverse habitats. Chameleons are accustomed to climbing, visual hunting; they have excellent vision, seeing up to 32 feet in front of them. This makes it easier to see the prey. This article outlines a step-by-step process for using CSOA to acquire proper MRSCNN values. In order to optimize the optimal MRSCNN parameters, a uniformly distributed population must be created. The entire step method is then presented in below,

3.5.1 Stepwise process of CSOA

The stepwise process is defines attain optimal values of MRSCNN using CSOA. Initially, CSOA makes uniformly distributed population for enhancing optimal parameters of MRSCNNparameters. Optimal solution is promoted utilizing CSOA method then equivalent flowchart is present in fig 2. Procedure of complete stage is given as following,

Step 1: Initialization

Initial population of CSOA is, initially generated by randomness. Initialize a chameleon population with random placements in the search space.Then the initialization is derived in equation (16),

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$$C = \begin{bmatrix} C_{1,1} & C_{1,2} \dots C_{1,n} \\ C_{2,1} & C_{2,2} \dots\dots C_{1,n} \\ \dots & \dots \quad \dots \\ C_{n,1} & C_{n,2} \dots C_{n,dis} \end{bmatrix} \tag{16}$$

Where, Z represents the location of CSOA; n signifies the total amount of chameleons and dis indicates the distance among the wild chameleons andprey.

Step 2: Random Generation

The input limits are made at casually. Explicit hyper parameter condition determines the optimal fitness value selection.

Step 3: Fitness Function

It creates random solution from initialized ideals. It is calculated using optimizing parameter. Then the formula is derived in equation (17),

$$Fitness\ Function = optimizing\ [G_n \ \ and \ \ \xi_U] \tag{17}$$

In this step, G_n is used to increase accuracy, while ξ_U is used to decrease computational time.

Step4: Exploration Phase G_n

During the exploration phase, chameleons can successfully search their environment for possible prey since their eyes are able to move independently. Their capacity to see with both eyes at once allows them to see their surroundings from a broad viewpoint. The ability to separate from one another allows each eye to revolve, emphasis on location of prey simultaneously using equation (18),

$$a_{E+1}^{i,j} = \begin{cases} a_T^{i,j} + G_n \left(R_T^{i,j} - Z_T^j\right)S_2 + S2\left(z_T^j - a_T^{i,j}\right)S_1 & S_i \geq R_s \\ a_T^{i,j} + \mu\left(\left(u^j - q^j\right)S_3 - q_y^j\right)\operatorname{sgn}\left(Sand - 0.5\right) & S_i < T_r \end{cases} \tag{18}$$

Where, $a_{E+1}^{i,j}$ is the $R_T^{i,j}$ iteration step, new location of i^{th} chameleon in j^{th} dimension; $a_T^{i,j}$ is the chameleon's current location and μ is a parameter that diminishes with the number of iterations and is defined as a function of iterations.

Step5: Exploitation for optimizing ξ_U

Chameleons hunt and attack their prey when it approaches too closely. The best and most ideal chameleon, so the saying goes, is the one that approaches its victim. This chameleon utilizes tongue to attack its prey. Its location is somewhat modified because may drop its tongue twice much as its length. Such technique makes it easier for chameleons to find prey by efficiently capturing it using equation (19),

$$\gamma_{T+1}^{i,j} = \omega X_n + z1\left(\gamma_T^j - b_T^{i,j}\right)P_1 + \xi_U z2\left(S_T^{i,j} - b_T^{i,j}\right)P_2 \tag{19}$$

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Here, γ is the best position in the world that chameleons are currently aware of prey; $z1\ and\ z2$ are two positive constants; P are consistently generated random numbers among $0\ and\ 1$ and ω is the weight of inertia that decreases linearly with the number of iterations. X_n is used to increase accuracy, while ξ_w is used to decrease computational time.

Step 6: Termination

The weight stricture value of creator $G_n\ and\ \xi_U$ as of MRSCNN is optimized by utilizing CSOA; and it will repeat step 3 until it obtains its halting criteria $C = C + 1$. The MR-PSC-MRSCNN defectively assesses the quality of early analyzes for fault diagnosis fault of photovoltaic panelsby higher accuracy, reducing computational time and error.

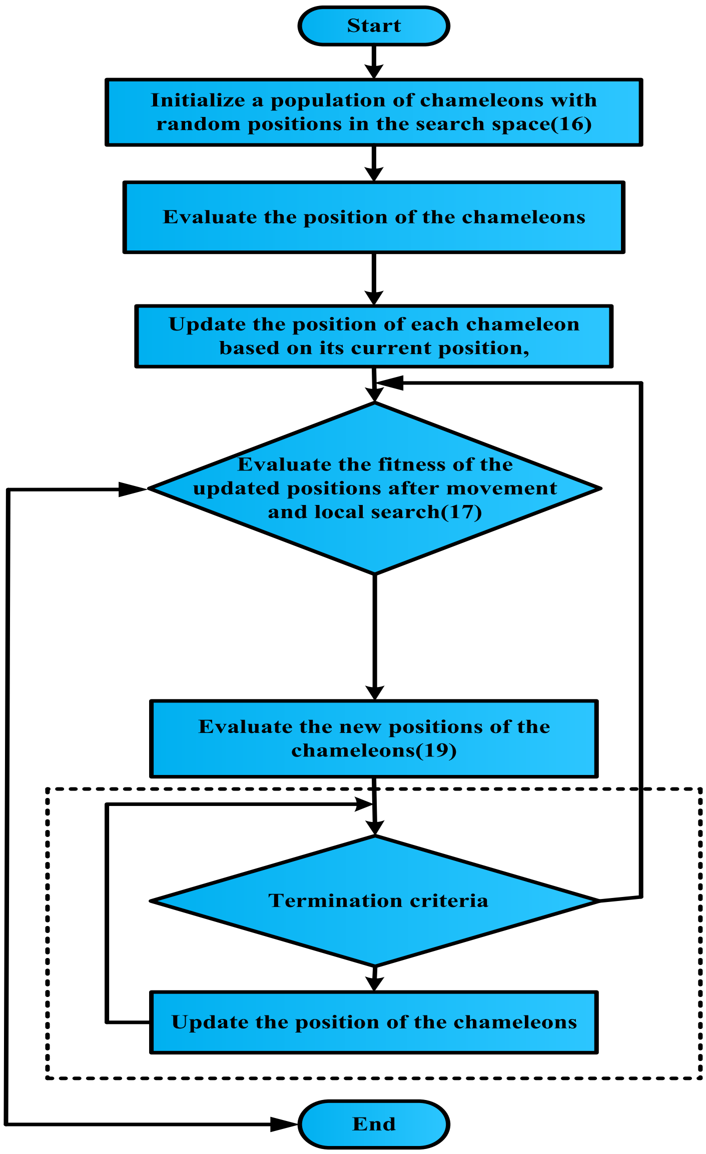

Figure2: Flow Chart of CSOA for Optimizing MRSCNN

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4.1 Performance Measures

It utilized to authorize performance of proposed technique. Performance measuresExactness, precision, f1-score, and sensitivity, specificity, and Error rate then Computation timeare evaluated. Measure act metrics, confusion matrix is deemed. Scale confusion matrix, the true negative, true positive, false negative and false positive values wanted.

4.1.1 Accuracy

Accuracy metrics the proportion of samples (positives and negatives) besides total samples and it is given by the equation (20),

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \quad (20)$$

Here, TP denotes true positives, TN indicates true negative, FP indicates false positive, FN signifies false negative.

4.1.2 Precision

Precision computes number of true positives divided through true positives plus number and false positives number and it given by the equation (21),

$$precision = \frac{TN}{FP + TN} \quad (21)$$

4.1.3 Specificity

Specificity estimates the proportion of negative samples and it is given by the equation (22),

$$specificity = \frac{TP}{FN + TP} \quad (22)$$

4.1.4 Sensitivity

Sensitivityfinds the proportion of positive models and it is given by the equation (23),

$$Sensitivity = \frac{TN}{TN + FN} \quad (23)$$

4.1.5 F1 Score

F1 Score denotes harmonic mean of precision, sensitivity and it given by equation (24),

$$F1\ score = \frac{TN}{TP + \frac{1}{2}\left[FP + FN\right]} \quad (24)$$

4.1.6 Error Rate

The rate of mistake is said to be the fraction of true positive cases to true negative cases that is incorrectly forecasted. Then the formula is derived in equation (25).

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$$ErrorRate = (1 - Accuracy) \tag{25}$$

4.1.7 ROC

The relation of false negative to true positive area, it is given by the equation (26)

$$ROC = 0.5 \times \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right) \tag{26}$$

4.2 Performance Analysis

Figure 3-8 depicts the simulation results of suggestedMMRSCNN-FD-SPVmethod. Then, the proposed MMRSCNN-FD-SPVmethod is likened with existing methods such as EE-FD-SP, LLF-CPV-EL and CNN-FC-PA respectively.

Figure 3shows accuracy analysis.To determine the defect detection system's advantages and disadvantages, the accuracy graph is examinedPrediction Accuracy in achieving the desired results. Different user experiences periods, such as months, semesters, or academic years, are represented by the X-axis. Every interval or point on the X-axis represents a distinct period of time that was used to generate and assess the forecasts. Prediction accuracy is represented on the Y-axis and is typically expressed as a percentage. It displays the percentage of accurate identifies produced over the course of each user experiences. Prediction accuracy used in the graph illustrates the trend of forecast accuracy over academic years. Here, MMRSCNN-FD-SPVmethod attains 28.57%, 32.45% and 26.45% higher accuracy for Fault-free system: 27.28%, 30.46% and 24.52% higher accuracy for string fault; 23.61%, 34.42% and 31.40% higher accuracy for string to ground fault; 35.14%, 35.43% and 27.48% higher accuracy for string to string faultanalyzed with existing technique likes EE-FD-SP, LLF-CPV-EL and CNN-FC-PA methods respectively.

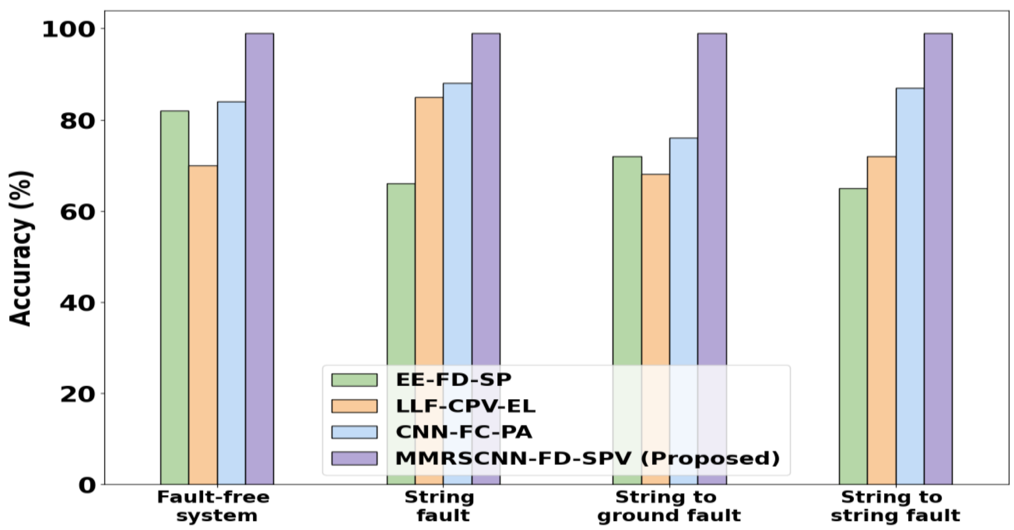

Figure 3: Performance Analysis of Accuracy

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Figure 4 shows precision analysis.The capacity of a detection approach to precisely locate and identify defects within the PV system is referred to as precision in fault detection. This could entail figuring out where defect detection works best or where adjustments are required.Here, MMRSCNN-FD-SPVmethod attains 28.39%, 34.15% and 23.65% higher precision for Fault-free system: 28.55%, 30.43% and 24.62% higher precision for string fault; 22.40%, 24.22% and 26.40% higher precision for string to ground fault; 31.54%, 35.23% and 25.53% higher precisionfor string to string faultanalyzed with existing technique likes EE-FD-SP, LLF-CPV-EL and CNN-FC-PA methods respectively.

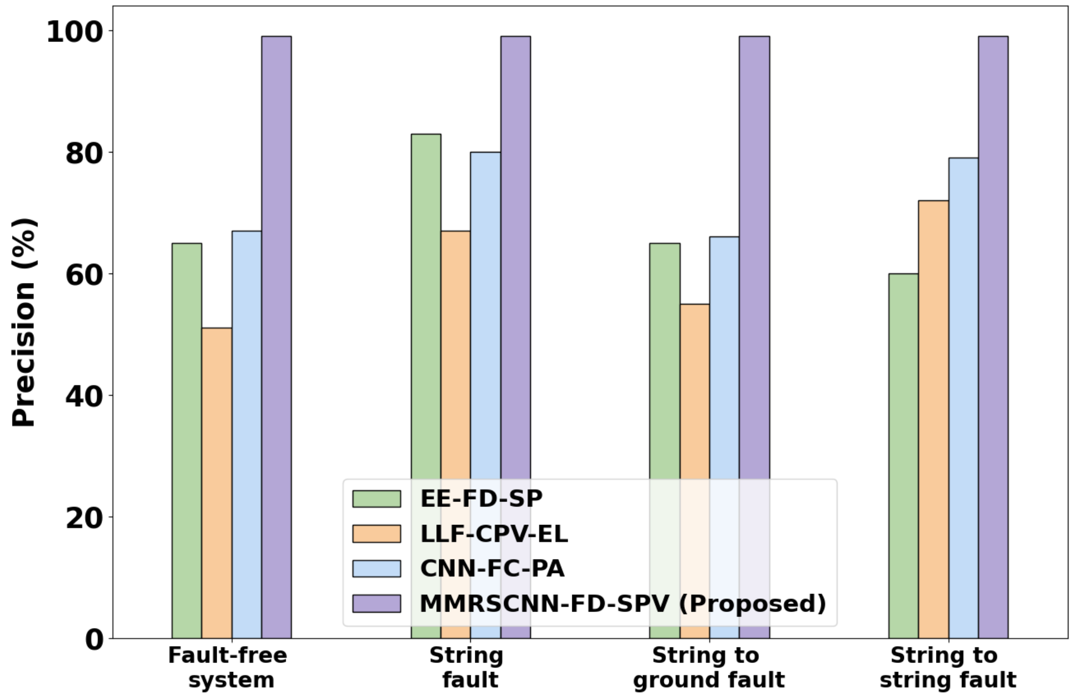

Figure 4: Performance Analysis of Precision

Figure 5shows f1-score analysis.It provides a balanced assessment of a system's capacity to identify errors while reducing false positives by accounting for both precision and sensitivity. When assessing the effectiveness of classification algorithms, such as defect detection systems in solar photovoltaic (PV) systems, the F1-score is a statistic that is frequently utilized. Here, MMRSCNN-FD-SPVmethod attains33.47%, 27.15% and 30.45% higher f1-scorefor Fault-free system: 273.45%, 28.43% and 23.52% higher f1-scorefor string fault; 25.40%, 31.42% and 26.30% higher f1-score for string to ground fault; 21.58%, 36.53% and 34.63% higher f1-score for string to string faultanalyzed with existing technique likes EE-FD-SP, LLF-CPV-EL and CNN-FC-PA methods respectively.

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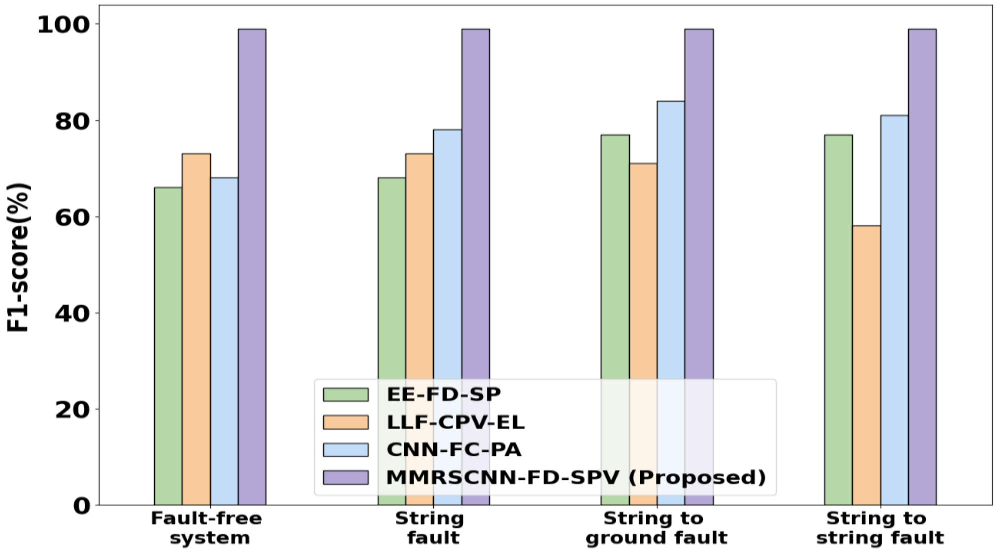

Figure 5: Performance Analysis of F1-score

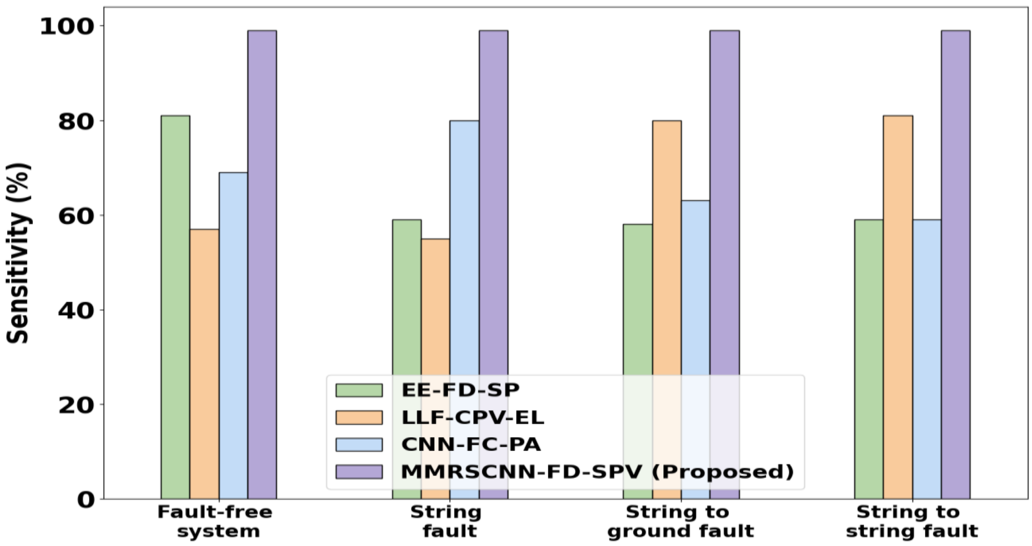

Figure 6: Performance Analysis of Sensitivity

Figure 6shows sensitivity analysis.The sensitivity is expressed as a percentage that shows how well the system can identify errors. Give each fault type a sensitivity value that represents the fault's level of accuracy that the system can detect.Here, MMRSCNN-FD-SPVmethod attains 27.57%, 31.25% and 31.15% higher sensitivity for Fault-free system: 26.45%, 32.63% and 23.49% higher sensitivity for string fault; 30.26%, 35.42% and 34.20% higher sensitivity for string to ground fault; 33.24%, 28.13% and 26.33% higher sensitivity

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for string to string faultanalyzed with existing technique likes EE-FD-SP, LLF-CPV-EL and CNN-FC-PA methods respectively.

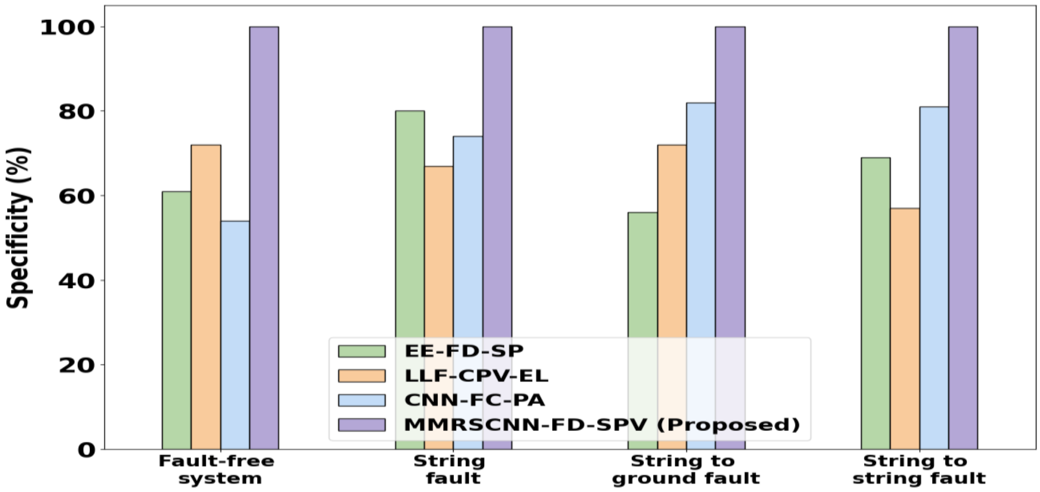

Figure 7: Performance Analysis of Specificity

Figure 7shows specificity analysis.Specificity is a metric used to quantify how well a fault detection system detects true negatives, or instances in which the system properly concludes that there is no fault. Here, MMRSCNN-FD-SPVmethod attains 32.17%, 24.55% and 34.45% higher specificity for Fault-free system: 25.50%, 31.43% and 27.42% higher specificity for string fault; 21.30%, 26.22% and 29.49% higher specificity for string to ground fault; 32.54%, 32.23% and 20.53% higher specificity for string to string faultanalyzed with existing technique likes EE-FD-SP, LLF-CPV-EL and CNN-FC-PAmethods respectively.

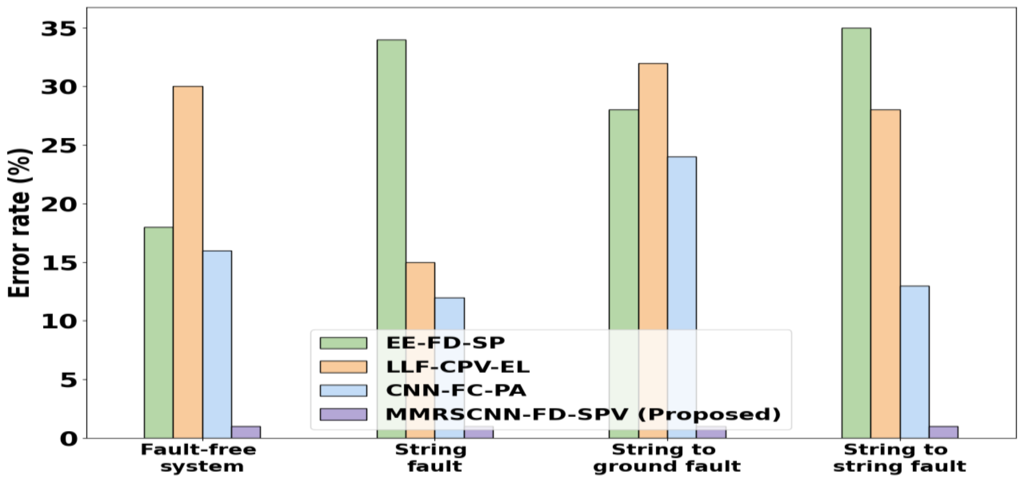

Figure 8: Performance Analysis of Error rate

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Figure 8shows error rate analysis.Each bar in this graph represents a separate defect category, and its height shows the category's error rateHere, MMRSCNN-FD-SPV method attains 12.47%, 20.40% and 24.33% lower error rate for Fault-free system: 28.12%, 21.11% and 28.12% lower error ratefor string fault; 20.10%, 26.02% and 22.50% lower error ratefor string to ground fault; 31.04%, 26.53% and 22.11% lowererror ratefor string to string faultanalyzed with existing technique likes EE-FD-SP, LLF-CPV-EL and CNN-FC-PA methods respectively.

4.3 Discussion

This manuscript proposed MMRSCNN-FD-SPV and summarizes a number of articles on the current state of research and advancement on the following five fronts: Numerous potential problems with PV boards, (ii) online/remote monitoring of PV boards, (iii) QCGAN function in PV panel fault diagnosis, (iv) a range of sensors utilized for different PV panel fault detections, and (v) MMRSCNNfor PV panel fault identification. From the perspective of fault categorization, a number of potential causes of faults were covered in detail, including errors in diodes-blocking and bypass diodes-as well as partial shading (PS), short circuit (SC), and open circuit errors (OCE). This study covered the numerous online methods designed to keep an eye on PV panel faults depend on the kind of sensor employed and PV panel checking.This research concluded by discussing the potential future direction and breadth of fault detection technique optimization. This can lower the time and expense involved in diagnosing solar power panel problems.

5. Conclusion

In this paper, MMRSCNN-FD-SPVis successfully implemented. The proposed MMRSCNN-FD-SPVapproach is implemented in python utilization of from Fault Detection Dataset. This model presented a novel monitoring technique that can reliably identify and categorize panel faults even in difficult situations that weren't covered by earlier research. This work suggested a deep learning procedure for identifying and categorizing panel faults in solar photovoltaic systems, depend on individual studyingprocedures and a probabilistic approach.The performance of proposed MMRSCNN-FD-SPV attains 21.30%, 30.59% and 24.57% higher Precision; 28.16%, 18.28%, and 34.50% higher f1-score; 27.75%, 20.19% and 30.57% lowererror rate are analyzed with existing methods like EE-FD-SP, LLF-CPV-EL and CNN-FC-PA respectively. Future work for the proposed MMRSCNN-FD-SPV will include investigating multi-modal data fusion to improve panel fault identificationaccuracy in complicated underwater environments and incorporating real-time adaptive learning techniques to improve model adaptability.This study would offer two critical features to plant owners who want to secure their plants' safety.

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