

MBO- S²-Serpentnet: A Novel Optimized Intelligent Fault Detection and Performance Monitoring Framework for Solar Energy Conversion Systems

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Abstract

A fault detection and monitoring mechanism is required to ensure reliable and consistent performance of a solar energy conversion system throughout its operational lifetime. The proposed framework uses Radial Basis Function Neural Network (RBFNN) controller for the Maximum Power Point Tracking (MPPT) system combined with a DC-DC boost converter. The RBFNN controller allows for maximum energy extraction from Photovoltaic (PV) systems with varying environmental conditions. An intelligent fault detection mechanism continuously monitors the electrical parameters of the PV module including voltage and current output to increase the dependability of the structure and provide a level of operational safety. A Deep Learning (DL) mechanism allows for optimizing the network using Monarch Butterfly optimization (MBO). The MBO process enhances the accuracy of fault classification of the proposed framework and the S²-SeRpEntNet enable robust identification of both early stages and critical stages of a fault during the lifetime of each fault. Preprocessing the data, performing feature extraction and normalizing are other steps that were taken to develop the accuracy of the predictions. The suggested system is implemented in MATLAB and achieved a higher accuracy of 0.99, precision of 0.98, Recall of 0.97 and F1-Score of 0.98. Hence, it deals with significantly enhanced energy efficiency, decreased power losses and improved long-term performance of solar energy conversion systems.

Keywords: PV system, S²-SeRpEntNet, MBO, RBFNN-MPPT, DC-DC boost converter.

1 Introduction

Technological progress and social evolution have increased energy consumption and created opportunities to increase fossil fuel produced energy on the planet [1]. The result is an increase in the quantity of carbon dioxide, emitted into the air through the sweltering of fossil fuels as a result of global warming, greenhouse gas emissions, and climate change, there has been an increased awareness of the issues created by burning fossil fuels and therefore a growing commitment to reduce fossil fuel produced energy on a global scale, which has translated to exponential growth and opportunity for the renewable energy sector and therefore renewable energy sources such as solar energy have seen exponential growth in market adoption for use in both residential and commercial applications. As of Q1 of 2020 NREL reported the amount of installed solar PV capacity at the end of 2019 was 627 GWDC, this was 115 GWDC above the previous year [2–4].

Regular maintenance of Solar PV systems is crucial for enduring performance. The maintenance strategy to monitor and maintain Solar PV systems is essential to provide the best performance over time. Many existing methods are available, for instance maintenance engineers use a number of the standard methods to perform preventative, corrective, and predictive maintenance [5]. Unfortunately, these standard methods are not very effective for detecting certain types of faults caused by low irradiance conditions, non-linear characteristics of output of PV modules and high fault

impedances. In response to these limitations, DC-DC converter is utilized [6]. In PV systems, DC-DC converters are adopted to regulate the DC voltage, which allows control of the operating point of the PV array and ensures that the extreme output power from the group is achieved. However, standard DC-DC converter cannot regulate the output voltage levels of a PV array for many variations in PV voltage caused by variations in solar irradiance, high temperature and load conditions. In many cases, conventional DC-DC converters cannot produce an output voltage at a higher and stable level than the load requires when the PV voltage drops below the required level [7–10].

Furthermore, the limited voltage gain and poor ability to adapt to a wide range of input voltages limit their ability to perform effectively for applications that rely on tracking the Maximum Power Point (MPP) [11]. To address these limitations of conventional DC-DC converters for PV applications, a DC-DC boost converter has been widely employed. The boost converter provides the ability to control the input impedance to the PV array by adjusting the duty cycle, which contributes to effective operation during tracking the MPP [12]. In PV systems, MPPT uses environmental factors like temperature and the intensity of light incident on the solar panel (solar irradiance) to determine the best location for extracting maximum power point. Incremental Conductance (INC) allows for rapid tracking MPP, then as the irradiance changes, both the MPP is tracked

quickly and steady-state oscillations are reduced. However, due to its relatively high computational complexity, the INC algorithm is highly dependent on accurate voltage or current measurements, [13–15]. The P&O approach is simple to implement and is low in computational expense. This is one reason that it is very popular with regard to MPPT. The major problem with the P&O is that it oscillates the MPP at steady state and change track direction during rapidly changing irradiance, which causes a degradation in its efficiency [16]. To overcome these limitations, the proposed system uses a RBFNN. The RBFNNs provide fast and accurate MPPT of the PV Systems by learning the nonlinear relationship between the environmental conditions and the PV output, thus allowing for faster response and reduced oscillations of power output [17].

In addition to this, a fault monitoring system is included in the PV system design, contributing a means to verify the reliability and safety of the PV system by monitoring the input informations collected such as the PV voltage, current, power, and converter output for any unintended changes from the expected ability of the PV system to perform normally [18]. To begin the modelling process, raw input data is collected, pre-processing such as data cleaning & denoising, and then visualised using technique such as heat-mapping to visually represent the relationship and patterns between the data features [19]. Key data features are extracted and normalised, to improve the accurateness of the machine learning method. The data is then divided into both testing and training to evaluate the method [20]. Then for model building, various conventional methods are illustrated in **Table 1**.

Table 1 Related works of existing conventional methods

Sl. No	AUTHOR /YEAR	MODEL	MERITS	DEMERITS	METRICS
1	Zeynep Bala Duranay et al [21]	Support Vector Machine (SVM)	Provide higher reliability of systems using an efficient algorithm with fewer amounts of data, and provide robust performance against high levels of noise.	Low scalability in terms of data size; and lack of explainability, making real time adaptation and fault diagnosis more complex.	It attains an accuracy of 0.93, precision, recall and F1-Score of 0.89
2	Syed Sikandar Shah et al [22]	Random Forest (RF)	The Random Forest method provides automatic feature importance detection, which helps to interpret and clarify the fault.	It requires a higher level of computational and memory resources, which reduces the efficiency of real-time deployment.	RF achieves an accuracy of 0.94, precision of 0.80, recall and F1-Score of 0.76.
3	Eiffat E Zaman et al [23]	Convolutional Neural Network (CNN)	CNN use electrical signals, thermal images and I–V characteristics to determine subtle faults at an early stage.	They lack the capacity to explain faults in present deployment of solar PV panels.	Accuracy, precision, recall and F1-Score for CNN are 0.92, 0.91, 0.89 and 0.90
4	Ghalia Nassreddine et al [24]	Decision Tree (DT)	It has fast computation with high interpretability, which allows for rule-based fault diagnosis of PV modules and inverter equipment to be performed with low computational cost.	It is highly sensitive to noise and random variations in the data from which the tree was constructed, and over fit to a large degree and it is often lower when used to classify complex nonlinear faults.	It accomplishes an accuracy, precision, recall and F1-Score is 0.97.
5	Shruti Kalra et al [25]	Artificial Neural Network (ANN)	It enables an accurate model of complex, nonlinear interactions among electrical and environmental parameters and thus an accurate prediction of both early and various types of faults in PV modules is monitored.	It requires a large amount of training data, extensive parameter selection, and significant computing resources.	ANN attains an accuracy of 0.98, precision of 0.97, recall of 0.94 and F1-Score of 0.95.

Present fault detection methods available for solar PV systems have shortcomings such as complex calculations, dependency on an enormous amount of

dataset, and unsuitability for environmental changes. Furthermore, they also have difficulty in discovering early faults resulting from the reasons such as partial

shading, low irradiance incidence, and nonlinear behavior of the PV mechanisms. Thus, an effective fault detection system is needed to ensure reliable real-time observation.

Because of the limitations of previously developed intelligent fault detection and performance monitoring (DT, SVM, RF, ANN, and CNN) methods, such as low adaptability to dynamic operating conditions, high computational complexity, high data dependency, low interpretability, and low real-time performance, the proposed system introduce a hybrid Spiking Neural Network (SNN) and S²-SeRpEntNet Model that overcomes all of these challenges. Finally, to optimize the parameters of the hybrid model, enhance convergence, create a stable system, and maximize detection accuracy, MBO is incorporated into the framework to produce a more robust, efficient, and accurate intelligent fault detection and performance monitoring framework for PV conversion structures. The system unites MBO technology with the S²-SeRpEntNet for generating exclusive results, wherein the MBO is utilized for optimizing the hyperparameter of the system while S²-SeRpEntNet employs its capability of detecting faults in the functioning of PV systems and carries out performance monitoring of the systems.

1.1 Contributions

- Establishing an MBO-S²-SeRpEntNet framework for intelligent monitoring of performance and fault detection in solar PV operation.
- Incorporating SNN with state-space selective resampling for processing temporal information leading to enhanced fault identification.
- Using MBO technique to accelerate model convergence and get the most effective results.
- Providing thorough comparison of the method against existing methods for proving reliability and accuracy of results overall and under different working conditions.

2 Proposed System Description

The proposed system integrates a PV power generation system and a data-driven predictive model designed for maximising energy extraction for accurate monitoring and fault detection. The PV system comprises a solar array, DC-DC Boost Converter and load, with continuous monitoring of voltage, current and power. The diagram of the suggested method is portrayed in **Figure 1**.

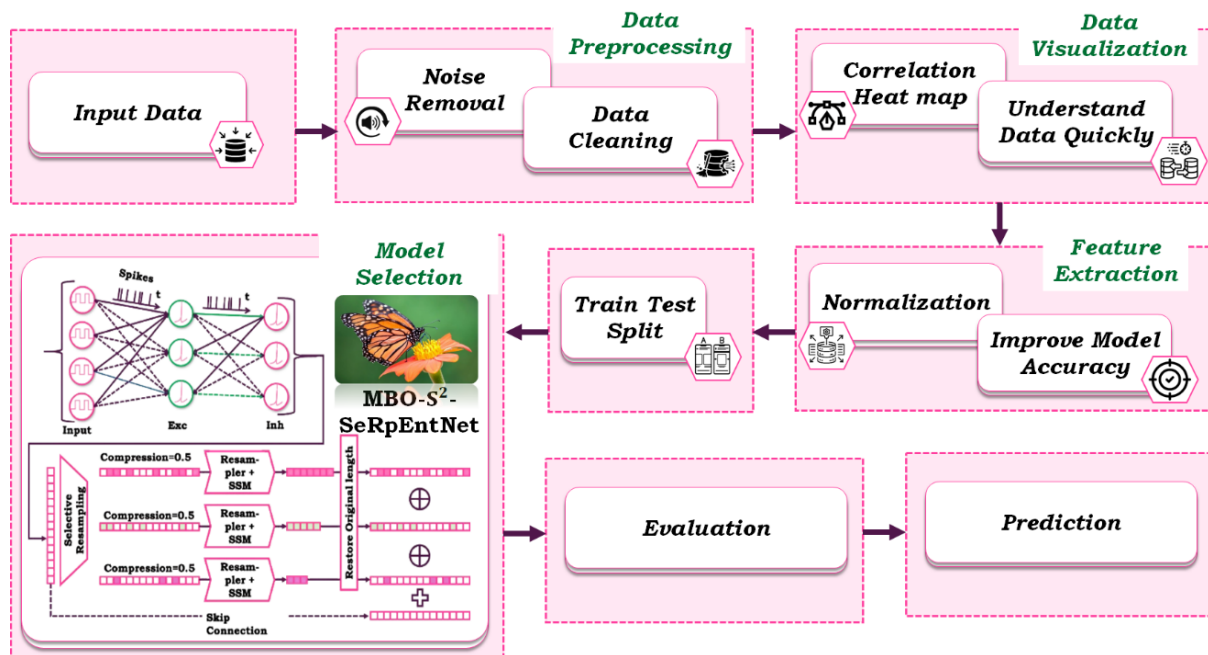


Figure 1 Proposed block diagram

RBFFN is used as the MPPT to allow for maximum harvesting of energy, using machine learning to learn the non-linear relationship between various environmental parameters such as solar irradiance, temperature and the PV output. This provides the capability of tracking the MPP, with fast and accurate tracking thereby reducing power oscillations and increasing the productivity of the complete structure. In addition, a real-time monitoring system gathers real-time electrical and environmental

parameters to detect anomalies and ensure reliable operation of a PV power generator. The machine learning workflow processes this data through a series of steps beginning with data cleaning, to noise removal, to visualisation, to feature extraction and finally to normalisation. The data sets are then divided into two categories and evaluated using traditional modelling techniques to assess accuracy of the predictions made. The hybrid MBO-S²-SeRpEntNet utilized a MBO for hyperparameter optimization of

the S²-SeRpEntNet, which is employed for intelligent fault detection and performance monitoring. The combined capabilities of this technology enhance the ability to extract PV energy more efficiently, to predict the future behaviour of PV systems and to detect the potential failures that occur due to varying environmental factors affecting PV performance.

3 Proposed System Modelling

3.1 PV conversion system for fault monitoring

Multiple diodes combined to create a PV Module for representation of the series connected solar cells within the module and these diode connections arranged parallel to represent multiple branches of solar cell connections in a module. Using the PV module's equivalent circuit to develop the equation for the output current is defined as follows Eq. (1):

$$I = I_{ph} - I_o \left(e^{\frac{V + I N_s R_s}{N_s V_{th}}} - 1 \right) - \left(\frac{V + I N_s R_s}{N_s R_{sh}} \right) \quad (1)$$

The thermal voltage is defined as Eq. (2),

$$V_{th} = \frac{nKT}{q} \quad (2)$$

Where, n is the diode ideality factor, k is the Boltzmann's Constant, T is the temperature in Kelvin and q is the electron charge. The equivalent circuit of RBFNN-MPPT controlled PV Boost converter system is shown in **Figure 2**.

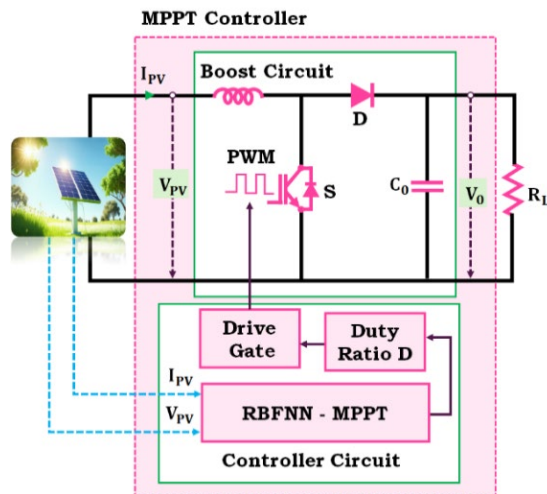


Figure 2 RBFNN-MPPT controlled PV Boost converter system

PV voltage and current are input to the RBFNN-MPPT Controller. The Controller uses this data to formulate an optimal duty cycle for maximum power point operation. This optimal duty cycle is then expressed as PWM pulses for controlling the switching of the DC/DC Boost Converter, which increases and stabilizes the PV output voltage. The stabilized DC voltage is subsequently delivered to the

DC load to provide optimal and dependable power delivery across a variety of environmental conditions. A DL based solution is proposed to enhance the accuracy of fault monitoring within the systems, thereby increasing system reliability.

The RBFNN works as a smart MPPT controller. It produces the required duty cycle for the DC-DC converter. It gets trained with the use of PV characteristics while the desired duty cycle is taken from the maximum power condition. Continuous feedback from the PV systems allows its stable operation in changing environmental conditions.

3.2 Data Preprocessing

It enhances the fault diagnosis and performance assessment by adding further assurance of the accuracy and precision of intelligent models. The first phase of preprocessing is data cleaning, in which missing values, outlier values, and inconsistent measurements due to sensor failures, communication failures, or environmental conditions are cleaned up from the data set. This ensures the consistency and integrity of the data, which in turn, will minimize misleading data patterns that would lead intelligence to make erroneous decisions related to diagnosing faults and assessing performance.

The second preprocessing phase involves removing any interference from noisy signals in the data obtained from PV systems resulting from irradiance variations, temperature fluctuations, power electronic switching, and measurement noise. Data is filtered and smoothed through the use of appropriate filtering techniques to eliminate any noise and retain information regarding real operational trends. When combined with data cleaning, eliminating noise enhances data quality, assisting the abstraction of accurate structures and improving both the reliability and accuracy of intelligent systems for fault diagnosis and performance monitoring regarding solar energy conversion systems.

3.3 Data Visualization

The intelligent problem identification and presentation monitoring framework for solar energy conversion systems includes data visualization as an essential component for interpreting large volumes of operational PV data and quickly understanding the behaviour of the system. In order for monitoring algorithms, a clear view of parameters like voltage, current, power, irradiance, and temperature vary with different functional environments, technologists visualize the data using visualization techniques such as plots and graphs. The use of graphical representations allows for the early identification of abnormal patterns, which indicate potential faults and performance degradation, such as sudden drops in power, deviations of voltage, or irregular fluctuations in current.

By visualizing data in correlation heat maps, and to identify the relationship between key PV parameters and environmental factors disturb the performance of the structure and the likelihood of faulting. The

identification of strong or weak correlations of PV parameters aids in identifying the key PV parameters most sensitive to fault occurrences. Additionally, the combination of data visualizations with correlation heat maps provides quick access for the system to work and allows for improved performance monitoring, enhanced accuracy and interpretability of intelligent problem identification and performance monitoring models for solar energy conversion systems.

3.4 Feature Extraction

With regard to the intelligent error identification and operation monitoring framework for solar energy conversion systems, the process of feature extraction is focused on extracting only relevant and distinct features that is obtained from initial pre-processed PV data. Important features represent the efficiency of a solar energy conversion system for operating parameters include voltage-current characteristics, variability of power output, efficiency ratings, temperature coefficients, and various statistical measures.

By removing redundant data and enhancing the recognition of abnormal fault signatures by the intelligent algorithms employed in the solar energy conversion system, effective feature extraction greatly increases the ability of the algorithms to distinguish amongst usual operation and the different kinds of failures. After extracting the features and removing redundant information, the normalization of the extracted features is performed, which scales the features to the same numerical value range. By doing this, the features with the largest numerical value are not dominate the training of the intelligent models used for both the error recognition and performance evaluation of the solar energy conversion systems.

Normalizing features increases numerical stability and accelerates convergence speed while increasing the ability for intelligent models to generalize results. This means that normalizing features significantly improve the accuracy, dependability, and robustness.

3.5 Model Selection- S²-Serpentnet

The SNN proposes the implementation of SNN in order to provide an effective method for modelling the time-dependent characteristics and event-driven behaviours associated with PV system data. The method employed to train SNNs in this work is through the conversion of ANN. There were a variety of methods available for training SNN to read PV system data, however the selected conversion method provides advantages in terms of scalability and being able to provide fault detection capability on multiple PV systems simultaneously. The conversion process is based on the functional equivalence between ANNs using ReLU neurons and Integrate and Fire (IF) spiking neurons. The synaptic dynamics of the IF neuron is listed below Eq. (3),

$$v_{mem}(t+1) = v_{mem}(t) + \sum_i w_i X_i(t) \quad (3)$$

The value of w_i indicates the amount of synaptic weight applied to a given input, while $X_i(t)$ is a timestamp associated with the incoming spike.

Algorithm 1 represents the Spiking + State-Space Selective Resampling Network.

Algorithm 1 Spiking + State-Space Selective Resampling Network

```

1: Initialize random seed
2: Normalize input features using Min–Max scaling
3: Split dataset into training and testing sets
4: Initialize Encoder layer (Linear)
5: Initialize LIF Spiking Neuron with threshold  $\theta$  and decay  $\lambda$ 
6: Initialize State-Space parameters A and B
7: Initialize Selective Resampling Gate
8: Initialize Binary Classifier
9: for epoch = 1 to E do
10:   Encode input features:
11:    $H \leftarrow \text{Encoder}(X)$ 
12:   Replicate encoded features across time:
13:    $H\_T \leftarrow \text{repeat}(H, T)$ 
14:   Initialize membrane potential  $M = 0$ 
15:   for  $t = 1$  to  $T$  do
16:     Update membrane:
17:      $M \leftarrow \lambda \times M + H\_T[t]$ 
18:     Generate spike:
19:      $S[t] \leftarrow 1$  if  $M \geq \theta$  else 0
20:     Reset membrane after spike
21:   end for
22:   Initialize hidden state  $h = 0$ 
23:   for  $t = 1$  to  $T$  do
24:     State update:
25:      $h \leftarrow \tanh(Ah + BS[t])$ 
26:     Store state  $h[t]$ 
27:   end for
28:   Compute resampling weights:
29:    $w \leftarrow \text{sigmoid}(\text{Gate}(h))$ 
30:   Select informative states:
31:    $h\_selected \leftarrow h \odot w$ 
32:   Temporal pooling:
33:    $h\_avg \leftarrow \text{mean}(h\_selected)$ 
34:   Predict output:
35:    $\hat{y} \leftarrow \text{sigmoid}(\text{Classifier}(h\_avg))$ 
36:   Compute loss using Binary Cross Entropy
37:   Backpropagate gradients
38:   Update parameters using Adam optimizer
39: end for
40: Evaluate model on test data
41: Compute Accuracy, Confusion Matrix, Classification Report
End Algorithm

```

When the generated output spike occurs is when the membrane potential at that instant is higher than a predetermined threshold, denoted as v_{th} . To model the expected output firing proportion of the IF neuron, the

expected firing rate of the incoming spikes is specified as $E[X(t)]$, thus Eq. (4)

$$E[Y(t)] = \frac{wE[X(t)]}{v_{th}} \quad (4)$$

The expected output firing rate is totally equivalent to the ReLU activation function. Due to this

equivalence, the previously trained neuro-anatomic models on voltage, current, power, and environmental input data is converted into SNNs with only minimal reduction of accuracy and, as a result of the sparse nature of spikes, increased energy efficiency in the error detection. The diagram of S²-SeRpEntNet is illustrated in **Figure 3**.

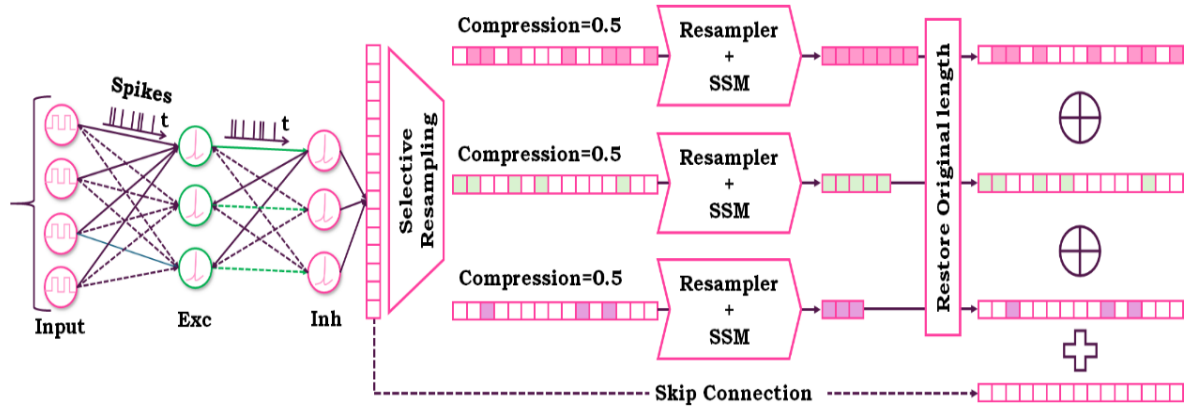


Figure 3 Architecture of S²-SeRpEntNet

To improve the temporal dependency modelling and avoid redundant computations, the State-Space Selective Resampling Network (SeRpEnt) is incorporated into the framework. With SeRpEnt, calculate adaptive time intervals from input PV time-series sequence $\{x_l\} | l \leq L$. The calculation of the adaptive time intervals is provided by the following equation Eq. (5).

$$\Delta_l = \sigma(\theta_\Delta(x_l))\Delta(1 - k) + k\Delta \quad (5)$$

In this equation, the function $\sigma(\cdot)$ is defined as the sigmoid function, the matrix θ_Δ is a learnable matrix transformation applied to the input PV time-series sequence, Δ is the learnable base of the adaptive time intervals and k defines the time interval compressed. Using the calculated time intervals, it resamples the original time-series $\{x_l\} | l \leq L$ into a compressed representation $\{\bar{x}_l\} | l \leq \bar{L}$ where all resampled values occur at uniform time intervals Eq. (6).

$$\bar{x}_l = \theta_\Gamma \left(\bigoplus_{t_k \in N_K(\bar{t}_1)} [x_k, \epsilon(\bar{t}_1 - t_k)] \right) \quad (6)$$

Where, $N_K(\cdot)$ is the set of K nearest neighbors of the resampled value of the original signal and $\epsilon(d)$ is the Gaussian basis expansion of the temporal distance from the original time-series sequence to its resampled neighbor, and is given by Eq. (7)

$$\epsilon(d) = \exp(-(d - \mu_i)^2) \quad (7)$$

After the compressed sequences processed by the state-space models, they are decompressed through

reverse resampling and concatenated with the original sequences using skip connections. The Spiking + SeRpEnt hybrid architecture allows to model both the short-duration faults and long-duration degradation events accurately, thus yielding an improvement in detection strength, computational efficiency and robustness.

3.6 Monarch Butterfly Optimization

MBO is used in this study due to its good balance between exploration and exploitation, rapid convergence features, and low likelihood of falling into local optima. These advantages make it highly effective for the optimization of complicated and non-linear parameter space related to detection of PV faults and monitoring of performance compared to more traditional optimization methods. The MBO method is proposed as a framework for monitoring and detecting faults and uses the seasonal migration of monarch butterflies as an analogy for dividing the search space into two separate habitats. Each butterfly in the MBO population stands for a candidate solution, and each individual butterfly is assigned to one of the two habitats according to the fitness function. The MBO population consist of two subpopulations.

The size of each subpopulation is determined by the number of butterflies (NP) and a parameter value (p) indicating the proportion of butterflies that migrate between the two habitats. The migration operator, which moves butterflies between two habitats, allows for better global exploration within the MBO framework. There are two ways in which butterflies move between habitats. If the butterfly's random number (r) generated during migration is less than or equal to the migration ratio (p), then the next position is calculated as follows,

$$x_{i,k}^{t+1} = x_{r1,k}^t \quad (8)$$

Here, $r = rand \times peri$ is defined, where $peri$ represents the migration periods.

$$x_{i,k}^{t+1} = x_{r2,k}^t \quad (9)$$

Where, $r2$ represents the randomly selected butterfly. If r using this mechanism, it provides a means to search globally to locate optimum patterns of PV failure among different operating conditions. The Butterfly Adjustment Operator promotes improved local exploitation of a solution by allowing the best-performing butterfly to provide input into the rate modifications for new candidates being tested. Otherwise, when $rand \leq p$ is expressed as,

$$x_{j,k}^{t+1} = x_{best,k}^t \quad (10)$$

The butterflies in a group are represented by x_{best}^t . Each butterfly represents the best solution found in the group.

$$x_{i,k}^{t+1} = x_{r3,k}^t \quad (11)$$

Where, $r3$ denotes a random number from Land 2. To further reduce the likelihood of premature convergence to a local optimum due to the typical issues associated with PV system fault detection and diagnosis, the butterfly updating process utilizes Lévy flight-based random walks and the method used for updating the position of the butterfly will depend on $rand > BAR$.

$$x_{i,k}^{t+1} = x_{j,k}^t + \alpha \cdot dx \quad (12)$$

The flowchart of MBO algorithm is depicted in **Figure 4**. The MBO methodology is used to tune the S²-SeRpEntNet model hyperparameter like learning rate, concealed dimensions and dropout rate. The process of optimization works with a predetermined size of the population and number of iterations. The classification accuracy is used as a fitness function for selecting the best parameter combination that leads to a better fault detection performance. Determines the form of the position update for this species where dx is equal to the step size of the Lévy flight and α is a weighting value. The stochastic nature of this process promotes exploration and therefore allows the optimization to exit from local minima. When applied within an intelligent fault detection and performance monitoring system, MBO provides increased convergence accuracy, improved robustness to local minima and increased performance across a broad range of data sets related to PV systems. MBO [26] provides for the optimization of fault detection models and allows for the accurate detection of faults, degradation trends, and abnormal operating conditions within solar energy conversion systems.

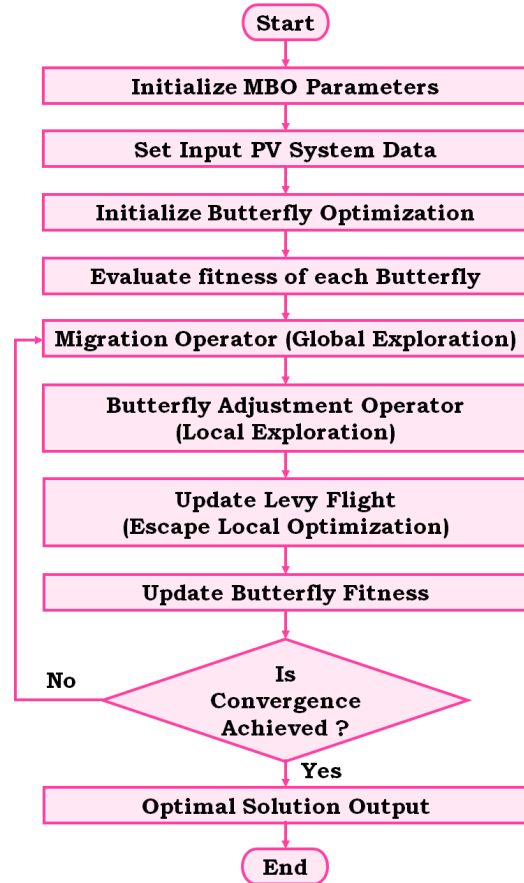


Figure 4 Flowchart of MBO algorithm

4 Result and Discussion

A simulation of a DC-DC boost converter was used to create a synthetic dataset to evaluate faults and normal operation of the converter. The boost converter was created in a simulated environment so that the operation would closely resemble to perform in the real-world under different scenarios. Since there is no publicly available fault data, a simulation approach was taken to provide a stable and reliable dataset for generating an accurate analysis of the fault diagnosis. The dataset consists of two types of operation, Healthy (normal) operation and Faulty operation. The fault class is considered the abnormal characteristics of the operation of a boost converter and includes typical failures of a boost converter such as failure of a component, switch, or sensor data. All the fault scenarios are included in creating typical disturbances that occur in the operation of a boost converter. The dataset is comprised of 1000 samples and is balanced across all two operation types. The data set is balanced; there are 500 samples in each class. The target variable are encoded using numerical representation and all numerical features are standardized before training the model.

Even if the data used in this study is obtained through the simulation process, it is representative of ordinary PV operational and fault conditions. The

focus of the next steps will be on testing the proposed methodology using real PV data.

Even if the suggested framework showed an excellent performance granted by a testing simulation, future studies will concentrate on confirming the correctness of the model by means of actual PV datasets, noisy conditions, and various fault levels to check the robust and reliable model.

This study used a dataset containing control, electrical and thermal data which consisted of Input Voltage, Output Voltage, inductor current, switch current, diode current, capacitor voltage, load current, duty cycle, temperature and ripple factor. These input parameters were identified as X and the output parameter was identified as Y which represented the fault or operating condition of the solar energy conversion system. For this study, a 70–30 train-test split approach was executed. 70% of the dataset was applied to train the models to identify faults, while 30% of the dataset was utilized to test the model's accuracy and generalization on an unseen dataset.

In **Figure 5**, the input voltages represent six equally sized segments (16.7% each) corresponding to the six input voltage values which are approximately between 18.4 volts and 24.8 volts.

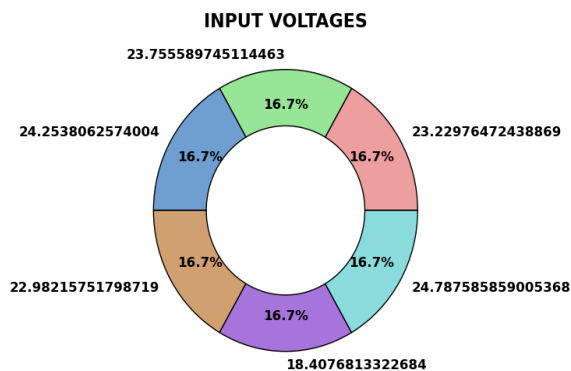


Figure 5 Input voltages

Figure 6 representing the frequency of occurrence for the three output voltage levels, approximately 42 volts, 46 volts, and 48 volts.

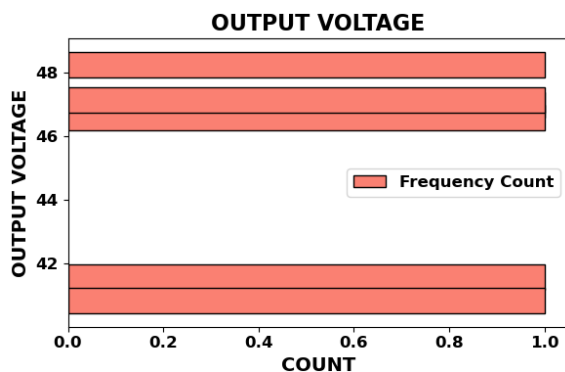


Figure 6 Output voltage

Figure 7 compares the input and output voltages categories. Each voltage appears only once. The output voltage is very high compared to input voltage.

COMPARISON OF INPUT VOLTAGE vs OUTPUT VOLTAGE

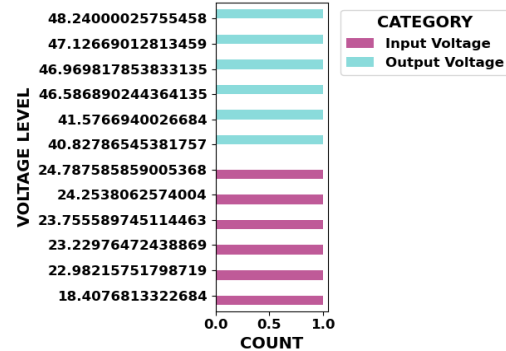


Figure 7 Comparison of input voltage and output voltage

In **Figure 8**, a histogram that includes a smooth density curve, show the distribution of switch current. The density curve shows a cluster of lower current but a gradual increase to the higher currents.

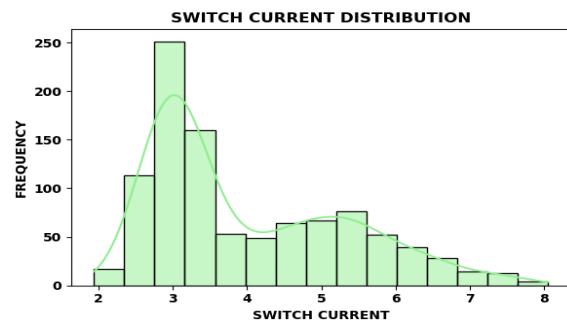


Figure 8 Switch current distribution

Figure 9 shows the pie chart displaying the current supplied to the inductor. The pie chart shows equal sections for each inductor current level so that all levels are contributing equally.

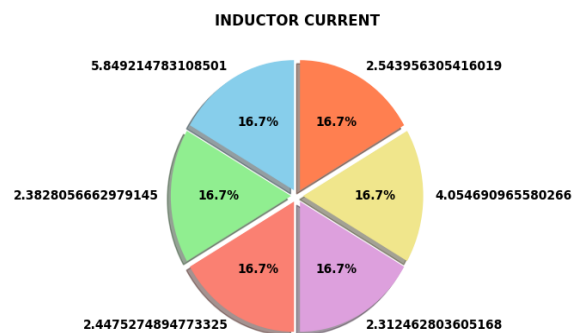


Figure 9 Inductor current

In **Figure 10**, a bar chart representing the frequency of labels, where the labels labelled as fault and no fault are represented in equal amounts. This suggests that there was a balanced dataset used to train the model.

In **Figure 11**, the confusion matrix indicates the model is upright because it accurately detects almost every case of both faults and non-faults with very few mistakes. Hence, the model has good accuracy, and fault detection is reliable.

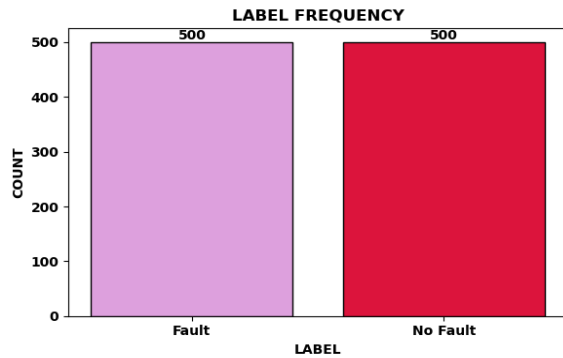


Figure 10 Label frequency

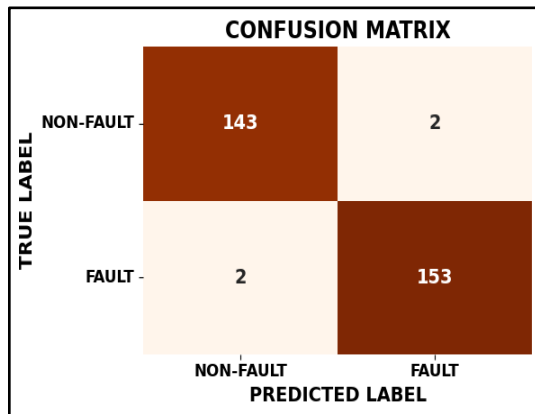


Figure 11 Confusion matrix

A line chart in **Figure 12** displaying the improvement of training vs validation accuracy and loss throughout each epoch, with both curves following closely together, which suggests an upright learning experience, with very little overfitting of the model.

Figure 13 shows the ROC curve which indicates that the model performs perfectly with a 1.0 AUC score and a high level of confidence in distinguishing between the fault cases and non-fault cases.

The obtained AUC value indicates that the dataset is well controlled and balanced. Future validations of the proposed methodology consider the application of real-world PV fault datasets with multiple different operating conditions.

Figure 14 indicates the evaluation metrics of Spiking and S²-SeRpEntNet, including a 99.0% accuracy, a 98.2% precision, a 97.85% recall, and an F1-score of 98.02%. This shows that the model produces highly reliable and balanced classifications.

In **Figure 15**, the model correctly classified as non-faulting case (141) and a faulting case (147), and only misclassified a very small number of cases (4 false alarms and 8 missed cases), indicating excellent accuracy performance of the model.

As per the findings of the 5-fold cross-validation, results in **Figure 16**, it shows that the model performs excellently with an accuracy of 98.60%–99.90%, which indicates reliable and generalizable. The consistent results throughout 5-fold cross-validation indicate a important capacity for generalization, but the goal of the future research is to test the proposed method under PV real-world operations.

- Here, several measures are used to improve the generalization capability of the proposed model.
- Specifically, the hidden dimension is reduced from 1024 to 512 to decrease model complexity.
- In addition, dropout regularization and early stopping are incorporated during training to mitigate overfitting.
- Furthermore, a 5-fold cross-validation analysis was conducted, yielding a mean accuracy of 99.27% with consistent performance across all folds.
- These additional experiments demonstrate that the proposed model learns generalized representations rather than merely memorizing the training data.

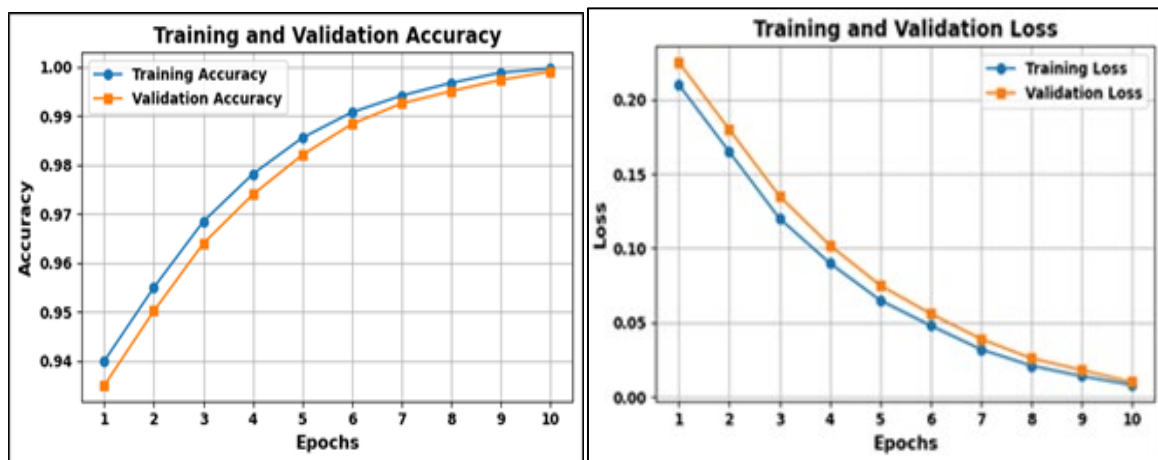


Figure 12 Comparison of training vs validation accuracy and loss

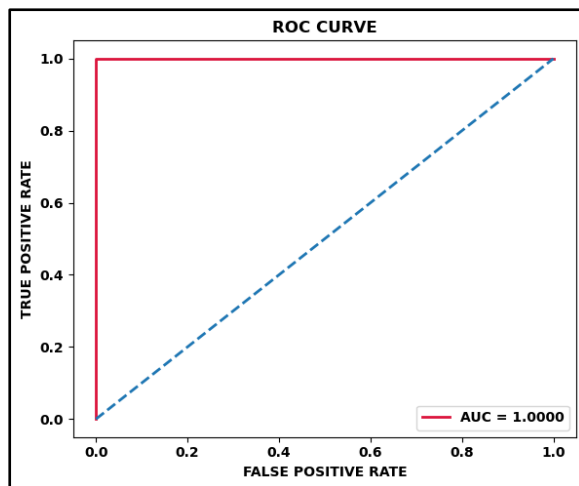


Figure 13 ROC curve

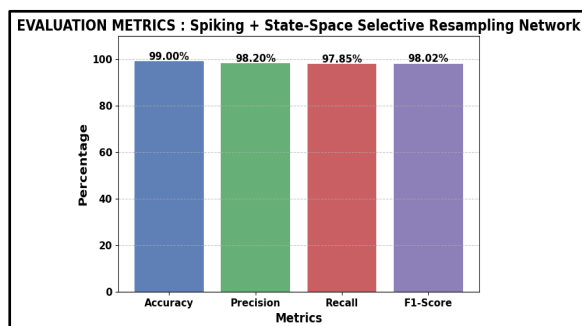
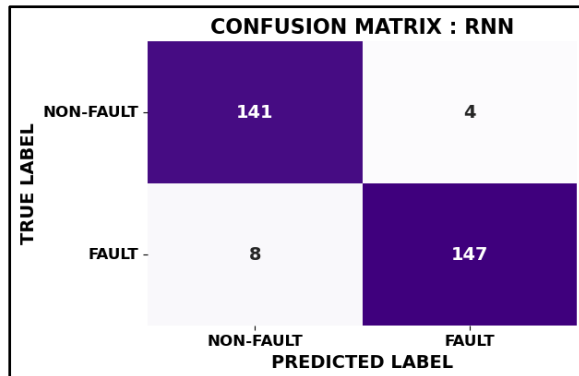
Figure 14 Evaluation of Spiking and S²-SeRpEntNet

Figure 15 Confusion matrix for RNN

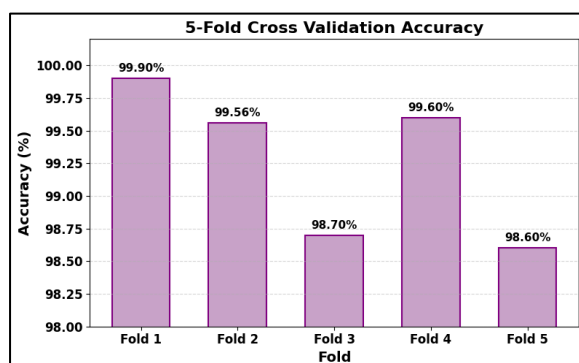


Figure 16 5-Fold cross validation accuracy

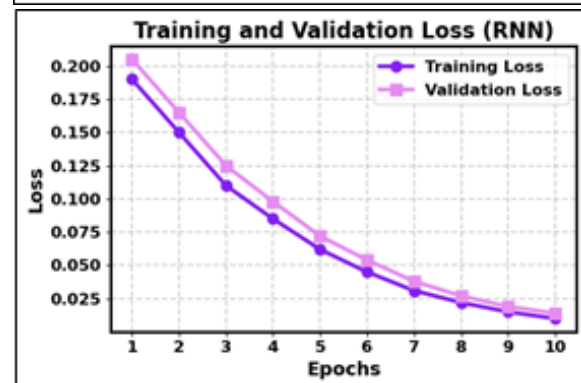
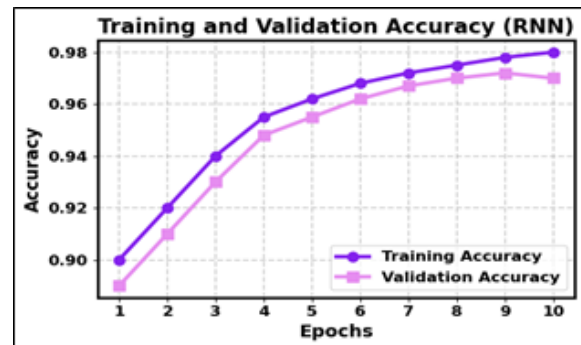


Figure 17 Training vs validation accuracy and loss for RNN

In Figure 17, RNN training and validation accuracy plots show a constant increase in both training and validation accuracy over 10 epochs. Training accuracy has grown from approximately 0.90 to over 0.98. Validation accuracy has grown from approximately 0.89 to around 0.97. Training and validation losses are decreasing, which indicates that the model has learned appropriately and converged well. There was very little risk of the model overfitting.

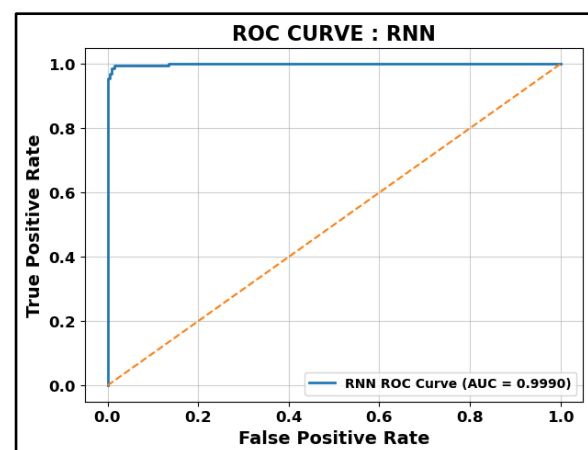


Figure 18 ROC curve for RNN

In Figure 18, the ROC Curve shows that the RNN Model has an almost perfect classification performance. It indicates the high capacity of the RNN model to discriminate between the available classes.

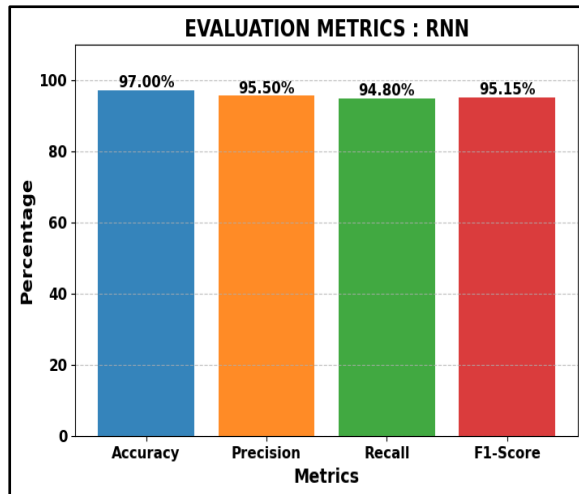


Figure 19 Evaluation metrics for RNN

Figure 19 shows that the RNN model's performance is evenly distributed, which demonstrates strong performance along with a very high value for all of the evaluation metrics accuracy, precision, recall, and F1score. Therefore, it is assumed that the RNN model is capable of providing high levels of accurate predictions while providing an effective balance of identifying correctly positive cases and minimizing false positives.

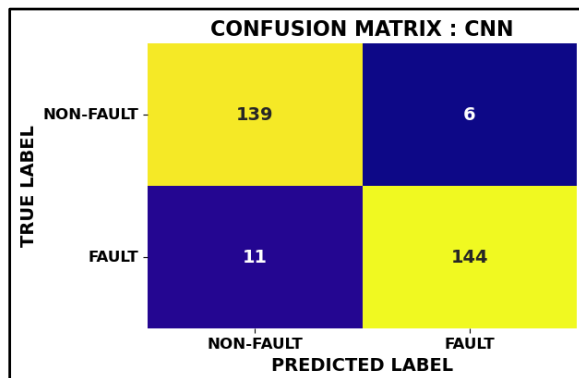


Figure 20 Confusion matrix for CNN

The Confusion matrix in Figure 20 determines that the CNN method has demonstrated a high level of accuracy for its classification of both fault and non-fault instances. Therefore, the CNN model has an ability to provide reliable performance of fault detection and accurate prediction

In Figure 21, the training and validation accuracy plots demonstrate that the CNN model is able to learn effectively over the epochs, showing that the CNN model is able to generalize well for overfitting. The training loss and validation loss, indicates effective learning on the training data and stability in the convergence of the CNN model.

The ROC curve illustrated in Figure 22 indicates that the CNN model has strong classification performance, which demonstrates a good capability of the method to differentiate amongst modules.

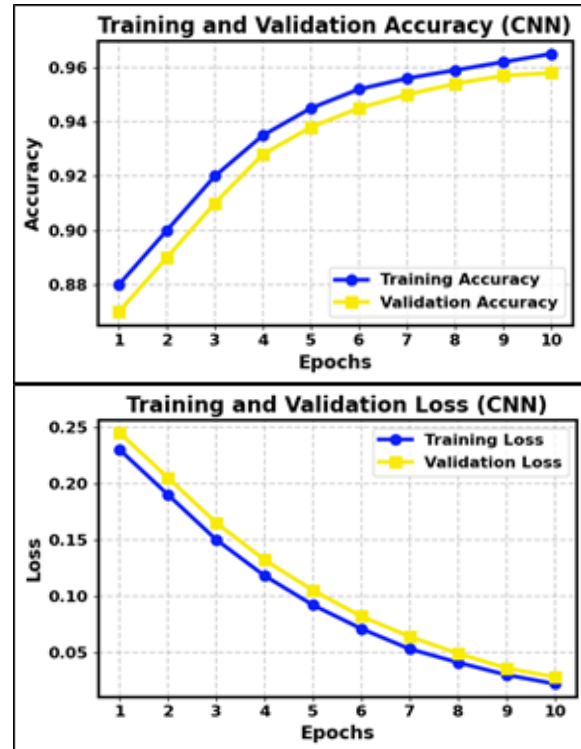


Figure 21 Training vs validation accuracy and loss for CNN

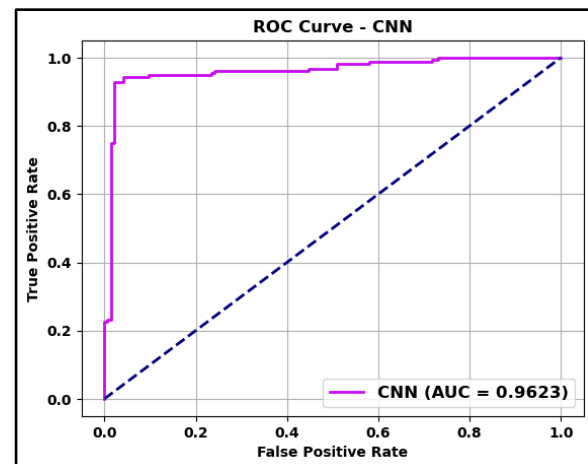


Figure 22 ROC curve for CNN

In Figure 23, according to the evaluation metrics, the CNN model demonstrates a high level of performance across all metrics, which indicates the ability of the model to classify and detect faults with minimal prediction errors.

In Figure 24, the comparison performance for the CNN and RNN models with the proposed method shows that the proposed method consistently exceeds the baseline models. This indicates that the proposed method is superior to the baseline models and produces better classified results

The proposed method provides the best overall performance, as indicated in the Table 2, exceeding both CNN and RNN models in all evaluation metrics.

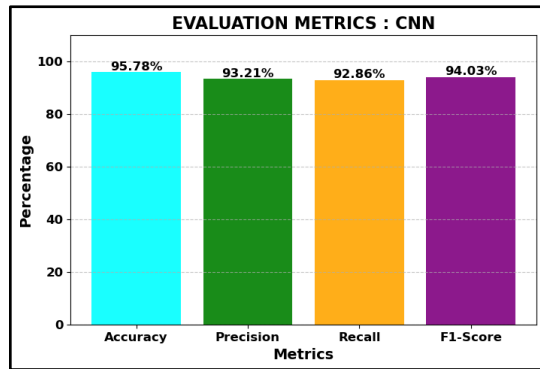


Figure 23 Evaluation metrics for CNN

Table 2 Model Performance Comparison

Sl.no	Model	Accuracy	Precision	Recall	F1-SCORE
1	CNN	0.9578	0.9321	0.9286	0.9403
2	RNN	0.9700	0.9550	0.9480	0.9515
3	PROPOSED	0.9900	0.9820	0.9785	0.9802

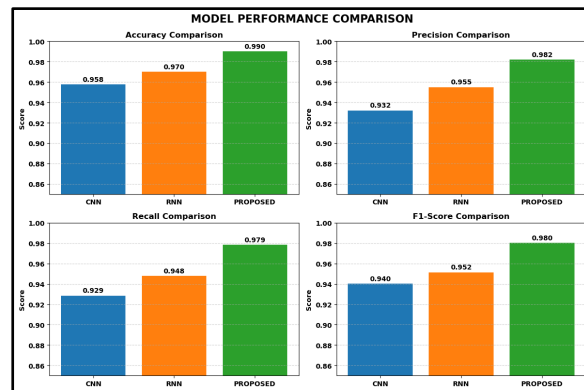


Figure 24 Comparison of model performance

Table 4 Ablation study

Model Variant	Hidden Units	Residual Blocks	Dropout	Optimizer	Weight Decay	Accuracy (%)
Without Residual Blocks	1024	0	0.15	AdamW	0.0001	97.86
Without Dropout	1024	4	0.00	AdamW	0.0001	98.34
Without Weight Decay	1024	4	0.15	AdamW	0.0000	98.62
Adam Optimizer	1024	4	0.15	Adam	0.0000	98.95
Hidden Dimension	512	4	0.15	AdamW	0.0001	99.12
Full Proposed Model	1024	4	0.15	AdamW	0.0001	99.60

Table 5 Comparison of accuracy for various methods

Sl.no	Model	Accuracy
1	CNN [23]	0.92
2	RF [22]	0.94
3	ANN [25]	0.98
4	PROPOSED	0.99

The proposed model provides the uppermost levels of precision compared to RF, CNN, and ANN in Figure 25. Therefore, the proposed model provides a better quality of fault detection than methods currently available.

In Table 3, the proposed method has a deeper architecture and more regularized architecture than the baseline models, and more hidden units in the architecture, GELU activation, Addams optimizer. The baseline models (RNN and CNN) are both less complex because they utilize Reule activation and Adam optimizer. The input features, batch size, and number of epochs used to train the models are kept the same across all three models.

Table 3 Comparison of Model Hyperparameters

Sl.no	Hyperparameter	Proposed	RNN	CNN
1	Input Features	4	4	4
2	Hidden Dimension/Units	1024	512	512
3	Residual Block/Layers	4	3	2
4	Dropout Rate	0.15	0.1	0.2
5	Output Neurons	1	1	1
6	Activation Function	GELU	ReLU	Tanh
7	Optimizer	AdamW	Adam	Adam
8	Learning Rate	0.0015	0.001	0.001
9	Weight Decay	0.0001	0	0
10	Batch Size	128	128	128
11	Epochs	10	10	10

The MBO-S²-SeRpEntNet model, which utilizes all of the design and optimization elements, has the greatest performance of every model listed in Table 4.

In Table 5, the outcomes show high confidence that the suggested process produce a much enhanced result than all previous models (CNN, RF, and ANN) with regard to accuracy in detecting faults.

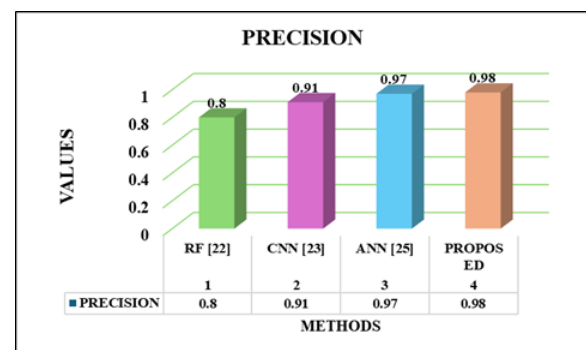


Figure 25 Comparison of precision

In **Table 6**, the recommended model attains the utmost levels of recall and F1-score, indicating that it is capable of effectively detecting faults and providing the most consistent level of classification accuracy across all categories of faults. As such, this model has proven to be more reliable and robust than both RF and ANN.

Table 6 Comparative analysis of Recall and F1-Score

Sl.no	Model	Recall	F1-Score
1	RF [22]	0.778	0.768
2	CNN [23]	0.89	0.90
3	ANN [25]	0.94	0.95
4	PROPOSED	0.97	0.98

The proposed model in **Figure 26** produces superior results across all metrics compared to RF, CNN, and ANN specifically, precision, recall, and F1-score. Therefore, it has a higher level of reliability and efficacy.

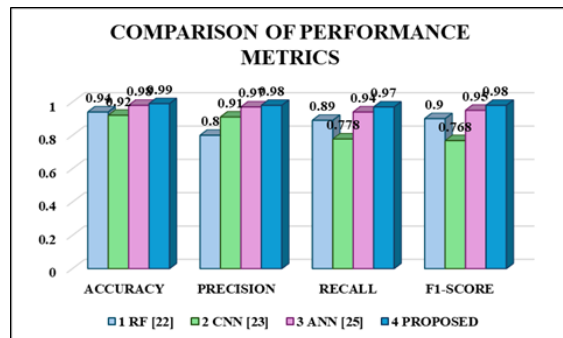


Figure 26 Relative comparison of metrics for performance

5 Conclusion

The proposed intelligent fault detection & performance monitoring framework based on MBO-S²-SeRpEntNet effectively integrates the physical modelling of solar PV systems with state-of-the-art data-driven technologies through all phases from signal acquisition through to final predictions. At the system level, the RBFNN-based MPPT has efficiently demonstrated its ability to remove the maximum amount of available energy from a Solar PV array despite variations in temperature and irradiance. In addition, the provision of a boost converter with PWM control provides stable DC outputs for efficient energy transfer to the loads and helps to maximise overall energy conversion efficiencies. Within the data process, through the use of preprocessing techniques such as cleaning and noise suppression, the data becomes more reliable for analysis and interpretation, while feature visualization and correlation analysis yield rapid information on the relationships between variables within the dataset. The processes of feature extraction and normalisation help to lower duplications and enhance the quality of features while increasing learning efficiency, which is achieved through an optimal separation of training/testing

datasets for reliable generalised prediction accuracy. The S²-SeRpEntNet is an optimally tuned neural network through MBO that classifies faults and monitors system performance better than traditional modelling methods due to its use of automatic tuning of network parameters, faster convergence and the inherent nature of avoiding local maximums. The proposed fault detection system demonstrates higher accuracy of 0.99, precision of 0.98, Recall of 0.97 and F1-Score of 0.98 compared to state of art models.

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