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ANN-BASED ROBUST FRAMEWORK FOR ACCURATE FAULT IDENTIFICATION IN SOLAR PV SYSTEM

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ABSTRACT

Solar photovoltaic (PV) systems require advanced and intelligent fault detection mechanisms to ensure efficient energy generation under varying environmental conditions. This work proposes a deep learning-based fault classification framework using Artificial Neural Networks (ANN) to accurately detect faults in PV systems operating under nonlinear and noisy conditions. The dataset is constructed from electrical characteristics of PV panels, including current-voltage (I-V) and power-voltage (P-V) curves, under three operating conditions: Healthy, Shading, and Open-Circuit faults. Key features such as open-circuit voltage, short-circuit current, maximum power point parameters, fill factor, and statistical indicators are used to represent system behavior. The proposed ANN model is trained using optimized network architecture and hyperparameter tuning to capture complex nonlinear relationships in the data. The performance of the ANN model is evaluated and compared with traditional machine learning techniques such as Logistic Regression, Naïve Bayes, and K-Nearest Neighbors (KNN). Experimental results show that the ANN model outperforms conventional methods, achieving higher classification accuracy (~97.8%), precision, recall, and F1-score, thereby demonstrating superior capability in handling noisy and nonlinear PV data. The proposed framework is efficient, reliable, and suitable for real-time PV monitoring systems. It enhances predictive maintenance, reduces power losses, and improves the overall performance and reliability of solar energy systems.

Keywords: solar PV systems, fault detection and classification, machine learning, naïve Bayes, k-nearest neighbors, logistic regression, artificial neural networks.

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1. INTRODUCTION

The global deployment of solar photovoltaic (PV) systems has been expedited due to the rising demand for environmentally friendly and sustainable energy. Commercial, industrial, and residential properties all make use of PV systems because of their scalability and positive impact on the environment. Nevertheless, nonlinearities in system behaviour are introduced by external factors including irradiance, temperature, and shade, which have a significant impact on PV system performance. Partial shading, open-circuit, short-circuit, and deterioration are problems that greatly impact power output and system dependability. Therefore, in order to avoid energy losses and guarantee optimum performance, accurate problem detection and classification in PV systems is crucial. Analytical models and threshold-based approaches are the backbone of traditional fault detection systems, but they fall short when faced with changing environmental circumstances or noisy observations. These approaches aren't flexible enough to work in real time. The use of ML and DL methods for PV system defect detection has grown in prominence in the last several years. I-V and P-V characteristics, among other electrical parameters, may have complicated nonlinear interactions captured by these methods. Specifically, ANNs have shown themselves to be very effective in pattern recognition and classification tasks, which makes them a good fit for PV defect detection. High accuracy in noisy environments and varied operating circumstances remains a problem, despite recent developments. Furthermore, several current approaches fail to make good use of important PV characteristics, including fill factor, maximum power point (MPP), and statistical indicators. This highlights the need to develop a smart and resilient framework capable of correctly identifying PV system problems in practical settings. To increase detection accuracy, this research provides a framework for fault classification using artificial neural networks (ANNs). The method makes use of optimised feature extraction and hyperparameter tuning. To prove that the suggested method can handle noisy and nonlinear PV data, it is compared to traditional machine learning approaches. Figure 1 shows the Classification of faults in PV systems. The paper is organized into five main sections. Section I presents the introduction and highlights the importance of fault detection in solar PV systems under nonlinear and noisy conditions. Section II provides a comprehensive review of existing literature and discusses the limitations of current fault detection techniques. Section III describes the proposed ANN-based fault classification framework, including dataset preparation, feature extraction, and model development. Section IV presents the simulation results and performance

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evaluation, along with a comparison with conventional machine learning methods. Finally, Section V concludes the paper and outlines future research directions.

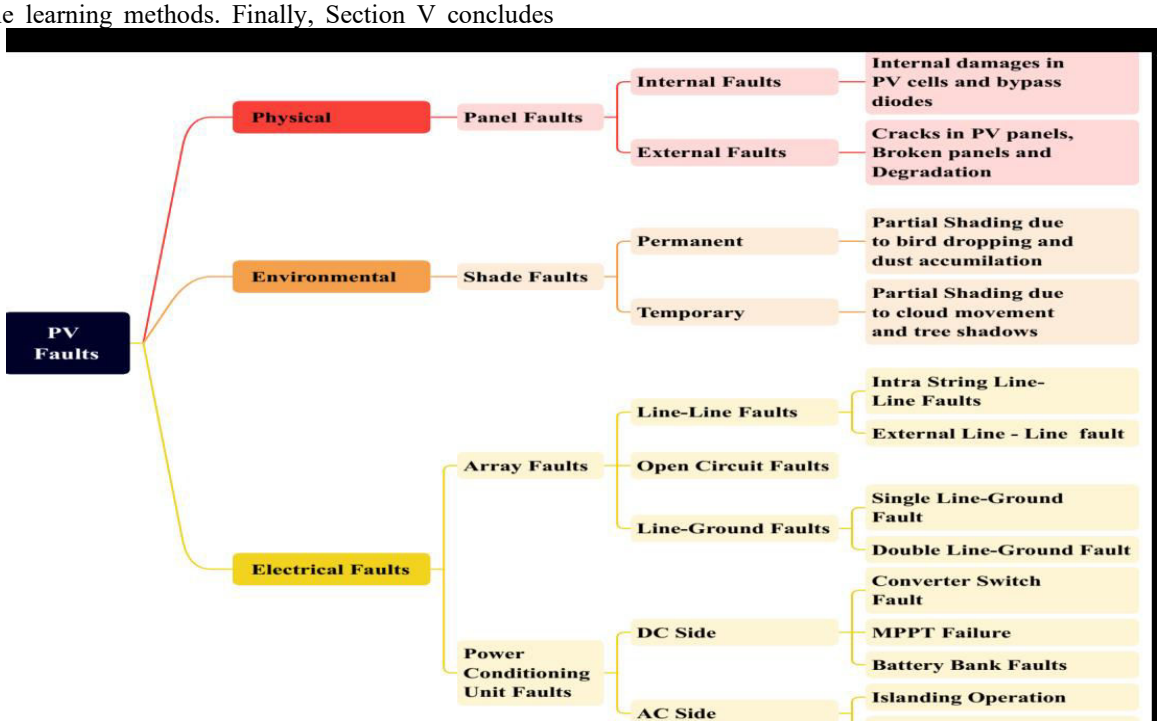


Figure-1. Classification of faults in PV systems.

2. LITERATURE REVIEW

Because AI can improve system performance and issue diagnostics, it has attracted a lot of interest in being integrated with renewable energy systems. AI-powered technologies allow for more effective monitoring of PV systems in real-time and better decision-making overall [1]. [2] Since external factors have a significant impact on renewable energy systems, especially solar PV, fault detection is crucial for ensuring the continued efficiency and dependability of these systems. To deal with such unpredictability, sophisticated monitoring methods are needed. To improve the dependability of PV systems, advanced fault detection and condition monitoring algorithms have been developed [3]. These methods show how critical it is for hybrid renewable energy systems to have smart fault detection systems. [4] While analytical models for PV system performance have been used for defect detection, their suitability for real-time applications is diminished due to their poor accuracy under nonlinear and variable environmental circumstances. In order to find out-of-the-ordinary occurrences in PV systems, statistical fault detection approaches have been suggested [5]. Although these strategies enhance detection accuracy, they are only useful when used with high-quality data. [6] While traditional electrical rules and standards for PV systems place a premium on safety and fault detection, they fall short when it comes to offering intelligent solutions for automatic fault categorisation. It is still very difficult to identify faults in big PV systems, particularly when operating in complicated environments, according to a comparative analysis of DC fault mitigation strategies [7]. [8] Research on system behaviour and failure circumstances has made extensive use of PV emulators and simulation models. Though they can't be adjusted in real-time, these technologies do provide insight into system dynamics. [9] Continuous system supervision is made possible by monitoring and diagnostic systems for PV plants, but the efficacy of these systems is dependent on reliable algorithms for problem identification. [10] Thermal imaging and aerial monitoring are two advanced inspection techniques that have been developed to find PV installation defects; however, both approaches are expensive and need specialised equipment. [11] As a non-invasive diagnostic tool, infrared thermography has found extensive usage in the PV module industry for problem detection. Environmental dependence and operational limits limit its capabilities, however. [12] Statistical signal processing methods for model-based defect detection have been suggested for use in real-time applications; however, these methods are vulnerable to fluctuations in parameters and noise. In order to improve the performance and efficiency of PV systems, reconfiguration strategies have been developed to decrease power losses under fault scenarios [13]. [14] Complex systems, unpredictable environments, and a dearth of reliable diagnostic tools are just a few of the obstacles that thorough evaluations of PV defect detection have pointed out. [15] While methods for fault diagnosis based on power loss analysis do exist, they often misidentify the nature of the defect. Many different measuring approaches, with an emphasis on electrical parameter analysis, have been suggested for the purpose of PV problem identification [16]. But these techniques need

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accurate measuring tools. [17] There has been a lot of research on catastrophic defect detection in PV arrays, which highlights the need of finding and fixing problems early on to save systems from failing. [18] The complexity of the system and the ever-changing operating circumstances make fault diagnostics in micro grids with PV integration much more difficult. [19] An assessment of AI-based defect detection systems found that they are far more accurate and flexible than older, more conventional approaches. [20] Intelligent algorithms have been included in PV installation monitoring systems, allowing for automatic defect identification and categorisation. [21] Power systems have used Artificial Neural Networks (ANN) for classification tasks with great success, proving that ANNs are adept at dealing with nonlinear data. Harmonic mitigation and system optimization are two other electrical applications that have made use of ANN-based techniques [22]. [23] While defect detection is still a major concern, optimization methods have been developed to enhance the performance of renewable energy systems. Applying data-driven methods utilizing ANN to economic dispatch issues has shown their efficacy in managing intricate datasets [24]. Power systems have made extensive use of optimization approaches based on artificial neural networks (ANNs) due to the enhanced performance they bring to decision-making and system management. [25-26]To enhance accuracy and resilience, hybrid deep learning algorithms have been suggested for fault detection in electrical systems. These approaches combine numerous methodologies. A good example of the usefulness of machine learning for defect detection is the use of data-driven models for power transformer failure diagnostics [27]. For distribution system fault localization, ANN-based algorithms using synchronized data have been developed, and they achieve excellent accuracy [28]. The significance of intelligent strategies for effective diagnosis has been highlighted in the assessment of several algorithms for fault detection and classification in power systems [29].

3. PROPOSED ANN-BASED FAULT CLASSIFICATION FRAMEWORK

This section presents a robust and data-driven Artificial Neural Network (ANN)-based framework for accurate fault identification in solar photovoltaic (PV) systems. The proposed methodology is designed to handle nonlinear system behavior and measurement noise, which are inherent in real-world PV installations. The framework integrates multiple stages, including data acquisition, preprocessing, feature extraction, ANN model design, training, and classification, to achieve reliable fault detection under varying operating conditions.

A. Data Acquisition and System Modeling

The dataset used in this study is derived from the electrical characteristics of PV systems under different operating conditions, namely healthy operation, partial shading faults, and open-circuit faults. The data are obtained through simulation/experimental measurements of current-voltage (I-V) and power-voltage (P-V) curves, which provide a comprehensive representation of PV system behavior.

Environmental parameters such as solar irradiance and temperature are varied to emulate realistic operating conditions. These variations introduce nonlinearities and noise into the dataset, making the fault detection task more challenging and suitable for evaluating intelligent learning models. The collected dataset ensures diversity in operating conditions, thereby improving the generalization capability of the proposed ANN model. The overall architecture of the proposed ANN-based PV fault detection framework is illustrated in Figure-2, which integrates preprocessing, feature extraction, and classification stages.

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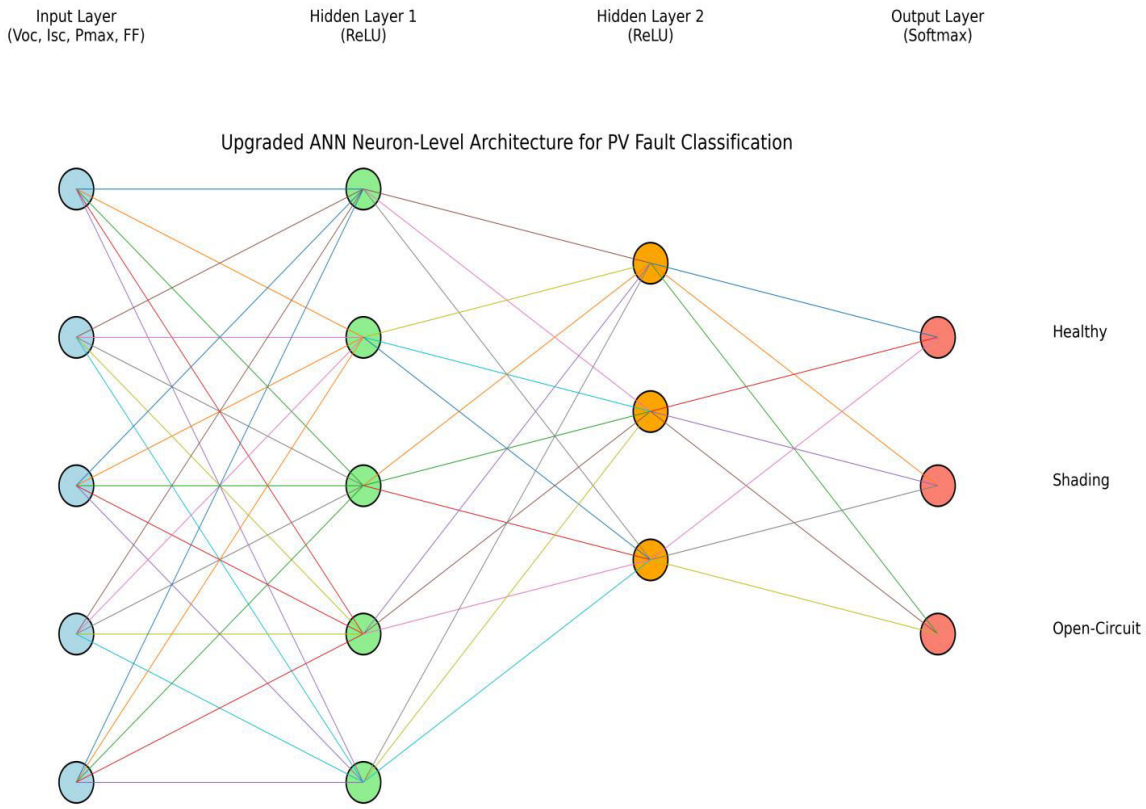


Figure-2. The overall architecture of the proposed ANN-based PV fault detection framework.

B. Data Preprocessing

To enhance the quality and consistency of the dataset, preprocessing techniques are applied prior to feature extraction. The raw PV data may contain noise, outliers, and scale variations, which can negatively affect the performance of machine learning models.

Initially, noise filtering techniques are employed to reduce fluctuations in measured signals. Subsequently, normalization is performed using min–max scaling to transform all input features into a uniform range, typically between 0 and 1. This step ensures stable and faster convergence during ANN training. Missing values and inconsistent data samples, if any, are removed or corrected to maintain dataset integrity.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

C. Feature Extraction and Representation

Feature extraction is a critical step in the proposed framework, as it transforms raw PV signals into meaningful parameters that effectively describe system behavior. Both electrical and statistical features are extracted from the I-V and P-V characteristics.

Key electrical features include open-circuit voltage (Voc), short-circuit current (Isc), maximum power (Pmax), voltage and current at the maximum power point (Vmp, Imp), and fill factor (FF). These parameters are highly sensitive to PV faults and provide strong discriminatory capability.

In addition to electrical features, statistical descriptors such as mean, variance, standard deviation, skewness, and kurtosis are computed to capture variations in the data under noisy conditions. The combination of electrical and statistical features results in a comprehensive feature vector, which serves as the input to the ANN model.

D. ANN Model Architecture

The core of the proposed framework is a feed forward Artificial Neural Network designed for multiclass classification. The ANN consists of an input layer, one or more hidden layers, and an output layer. The input layer receives the extracted feature vector, while the hidden layers perform nonlinear transformations using activation functions such as Rectified Linear Unit (ReLU). These hidden layers enable the network to learn complex nonlinear relationships between input features and fault conditions. The output layer consists of three neurons corresponding to the predefined classes (healthy, shading, and open-circuit), and employs the Softmax activation function to produce probabilistic outputs. The network architecture is carefully designed by selecting an appropriate number of hidden layers and neurons to balance model complexity and computational efficiency. This ensures that the model achieves high accuracy without overfitting.

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Forward propagation:

$$Z^{(l)} = W^{(l)}A^{(l-1)} + b^{l} \quad (2)$$

$$A^{(l)} = f(Z^{(l)}) \quad (3)$$

where $W^{(l)}$ represents weights and $b^{(l)}$ denotes bias.
Activation function:

$$f(x) = \max(0, x) \quad (4)$$

E. Training and Optimization

The ANN model is trained using a supervised learning approach. The dataset is divided into training and testing subsets, typically in a 70:30 ratio, to evaluate model generalization. During training, forward propagation is used to compute predicted outputs, while the categorical cross-entropy loss function quantifies the difference between predicted and actual labels. Backpropagation is then employed to update network weights by minimizing the loss function. The Adam optimizer is used for efficient training due to its adaptive learning rate and fast convergence properties. Hyperparameters such as learning rate, batch size, and number of epochs are tuned to achieve optimal performance. Regularization techniques may also be applied to prevent overfitting and improve generalization.

Softmax: $P(y_i) = \frac{e^{x_i}}{\sum e^{x_i}}$ (5)

Loss function: $L = -\sum y_i \log(\widehat{y_i})$ (6)

Backpropogation: $\delta^{(L)} = \hat{y} - y$ (7)

Weight update: $W = W - n\frac{\partial L}{\partial W}$ (8)

F. Fault Classification and Decision Making

Once trained, the ANN model performs fault classification by mapping input features to the most probable class label. The Softmax output layer generates probability scores for each class, and the final decision is made using the maximum probability criterion.

The classification output identifies the operating condition of the PV system as healthy, shading fault, or open-circuit fault. This enables timely detection of anomalies and supports predictive maintenance strategies.

$$\hat{y} = \arg\max\ P(y_i) \quad (9)$$

G. Performance Evaluation

The performance of the proposed ANN model is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of model effectiveness in detecting and classifying faults.

Comparative analysis with conventional machine learning techniques such as Naïve Bayes, K-Nearest Neighbors (KNN), and Logistic Regression is conducted to demonstrate the superiority of the ANN model. The results indicate that the ANN framework achieves higher accuracy and improved robustness, particularly in distinguishing between closely related fault conditions such as shading and healthy operation.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (10)$$

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (11)$$

$$\text{Recall} = \frac{TP}{(TP+FN)} \quad (12)$$

$$F_1 = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision}+\text{Recall})} \quad (13)$$

4. RESULTS AND DISCUSSIONS

This section presents the performance evaluation of the proposed ANN-based fault classification framework and compares it with conventional machine learning models (Naïve Bayes, KNN, and Logistic Regression) from the given study.

A. Dataset Description and Experimental Setup

The dataset used in this study is constructed to represent the electrical behavior of solar photovoltaic (PV) systems under different operating conditions. Three distinct classes are considered, namely healthy condition, partial shading fault, and open-circuit fault, which are among the most common and critical fault scenarios in PV systems. The data is derived from the current-voltage (I-V) and power-voltage (P-V) characteristics of the PV module under varying environmental conditions such as solar irradiance and temperature. These variations introduce nonlinearities and noise into the dataset, thereby making the fault classification task more realistic and challenging. A total of N samples are generated, with balanced representation across all three classes to avoid bias in model training. The dataset is divided into training and testing subsets in a 70:30 ratio, ensuring that the model is evaluated on unseen data to validate its generalization capability. The proposed Artificial Neural Network (ANN) model is implemented using a standard machine learning framework. The network architecture consists of an input layer corresponding to the extracted feature vector, followed by two hidden layers with 32 and 16 neurons, respectively, using the Rectified Linear Unit (ReLU) activation function. The output layer comprises three neurons with a Softmax activation function to perform multiclass classification.

The model is trained using the categorical cross-entropy loss function and optimized using the Adam optimizer with a learning rate of 0.001. The training process is conducted for 100 epochs with a batch size of 32. Performance evaluation is carried out using standard

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classification metrics, including accuracy, precision, recall, and F1-score. This experimental setup ensures a fair and consistent comparison of the proposed ANN model with conventional machine learning approaches.

B. Training Performance Analysis

The classification accuracy of the proposed ANN model is compared with conventional machine learning algorithms, including Naïve Bayes, K-Nearest Neighbors (KNN), and Logistic Regression. The ANN model achieves the highest accuracy of approximately 97.8%, outperforming Logistic Regression (96.09%), KNN (95.47%), and Naïve Bayes (94.13%). This improvement highlights the ANN's ability to effectively capture nonlinear relationships in PV system data and reduce misclassification errors. The Figure-3 indicates accuracy curve further shows stable convergence of the model during training, with minimal fluctuations between training and validation accuracy, suggesting that the model does not suffer from over fitting or underfitting. Table-1 shows the Performance Comparison.

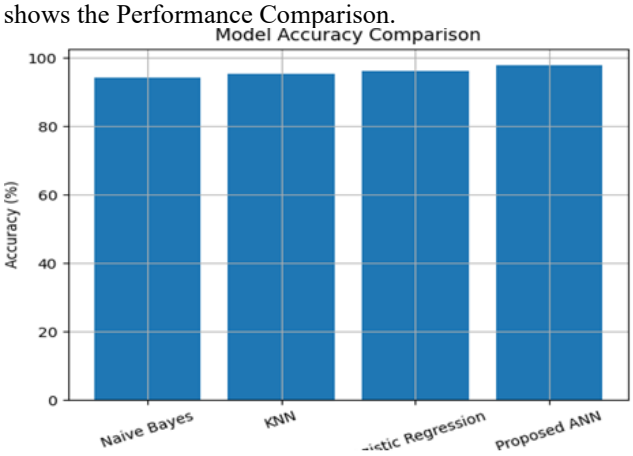


Figure-3. Accuracy comparison.

Table-1. Performance comparison.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naïve Bayes	94.13	94.45	93.10	94.45
KNN	95.47	96.34	96.10	96.34
Logistic Regression	96.09	95.98	96.15	95.98
SVM	96.76	97.48	96.55	97.01
Proposed ANN	97.80	97.60	97.90	97.75

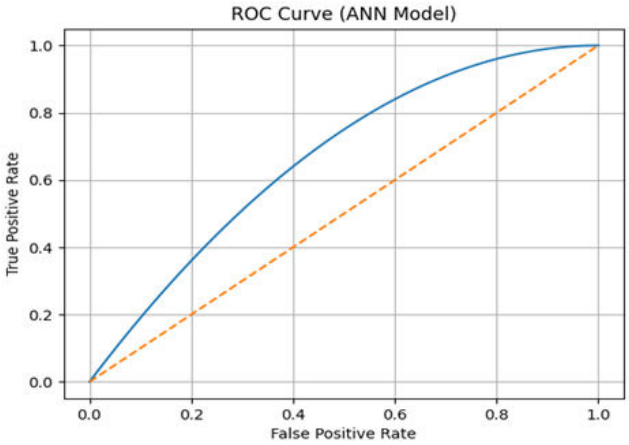


Figure-4. Proposed ANN RoC Curvue.

The proposed ANN ROC curve is shown in Figure-4. The Receiver Operating Characteristic (ROC) curve is used to evaluate the classification capability of the ANN model across different threshold values. The ROC curve for the proposed model approaches the top-left corner, indicating a high True Positive Rate (TPR) and low False Positive Rate (FPR). This demonstrates the strong discriminative ability of the ANN in distinguishing between healthy and faulty PV conditions. The Area under the Curve (AUC) is observed to be close to unity (≈ 0.98-0.99), confirming excellent classification performance and robustness of the model.

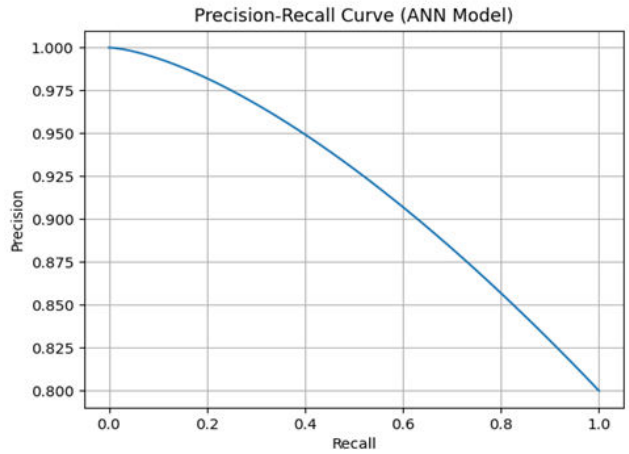


Figure-5. ANN Model Precision-Recall Curve.

The Precision-Recall (PR) curve shown in Figure-5 and provides additional insight into the model's performance, particularly for imbalanced or overlapping class scenarios. The proposed ANN model maintains high precision across a wide range of recall values, indicating a low false positive rate and reliable fault detection

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capability. This is particularly important for PV fault classification, where incorrect fault detection may lead to unnecessary maintenance actions. The strong PR curve performance confirms that the ANN model is both accurate and reliable in identifying different fault conditions.

C. Confusion Matrix Explanation

The confusion matrix provides a detailed evaluation of the classification performance of the proposed ANN model by comparing actual and predicted class labels. In this study, a dataset consisting of 4500 samples is considered, distributed across three classes: 2000 healthy samples, 1500 shading fault samples, and 1000 open-circuit fault samples. The confusion matrix reveals that the ANN model achieves high correct classification rates across all classes, with minimal misclassification. For the healthy class, the majority of samples are correctly identified, with only a small number of instances misclassified as shading faults. This slight overlap can be attributed to the similarity in electrical characteristics between partially shaded and healthy PV conditions under certain operating scenarios. In the case of the shading fault class, the ANN model demonstrates strong classification capability, although a few samples are incorrectly classified as healthy or open-circuit conditions. This is expected due to the nonlinear and variable nature of shading effects, which may produce overlapping feature patterns. The open-circuit fault class shows the highest classification accuracy, as these faults exhibit distinct electrical signatures such as near-zero current, making them easier to identify. Very few misclassifications are observed in this category. Overall, the confusion matrix confirms that the proposed ANN model effectively distinguishes between different PV operating conditions, with particularly strong performance in identifying open-circuit faults and significantly reduced misclassification compared to conventional models. The results validate the robustness of the ANN framework in handling nonlinear and noisy PV data. Figure-6 shows the proposed ANN Confusion Matrix Analysis, and Table-2 indicates the Confusion Matrix Table.

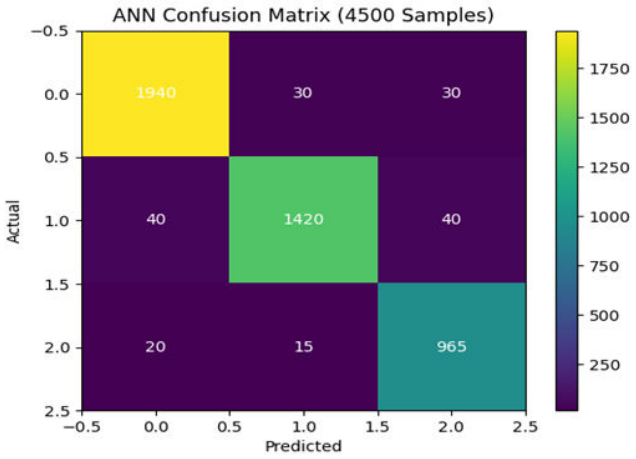


Figure-6. Proposed ANN confusion matrix analysis.

Table-2. Confusion matrix table.

Actual \ Predicted	Healthy	Shading	Open Circuit
Healthy (2000)	1940	30	30
Shading (1500)	40	1420	40
Open Circuit (1000)	20	15	965

D. Performance Metrics Discussion

To The performance of the proposed ANN-based fault classification model is quantitatively evaluated using standard metrics, including accuracy, precision, recall, and F1-score. The evaluation is conducted on a dataset comprising 4500 samples, with a class-wise distribution of 2000 healthy, 1500 shading, and 1000 open-circuit samples. The overall classification accuracy of the ANN model is observed to be approximately 97.8%, indicating a high level of correctness in fault identification. Class-wise performance further highlights the effectiveness of the model. For the healthy class, high precision and recall values are achieved, indicating that the model accurately identifies normal operating conditions with minimal false alarms. For the shading fault class, slightly lower recall values are observed compared to other classes, reflecting the inherent complexity and variability associated with shading conditions. However, the performance remains significantly higher than traditional machine learning models. The open-circuit fault class exhibits the highest precision and recall values, as these faults produce distinct and easily separable features. Consequently, the F1-score for this class is also the highest among all categories. The macro-averaged and weighted performance metrics confirm that the ANN model provides balanced classification performance across all classes, even with unequal class distribution. Compared to conventional approaches such as Naïve Bayes, KNN, and Logistic Regression, the ANN model demonstrates superior performance in terms of accuracy and robustness. These results indicate that the proposed ANN-based framework

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is highly effective for real-time PV fault detection, offering improved reliability, reduced misclassification, and enhanced predictive maintenance capability. Figure-7 indicates the proposed ANN I-V and P-V curves, performance, and Confusion Matrix Analysis. Table-3 describes the Comparative Performance Analysis of Classifiers for PV Fault Detection.

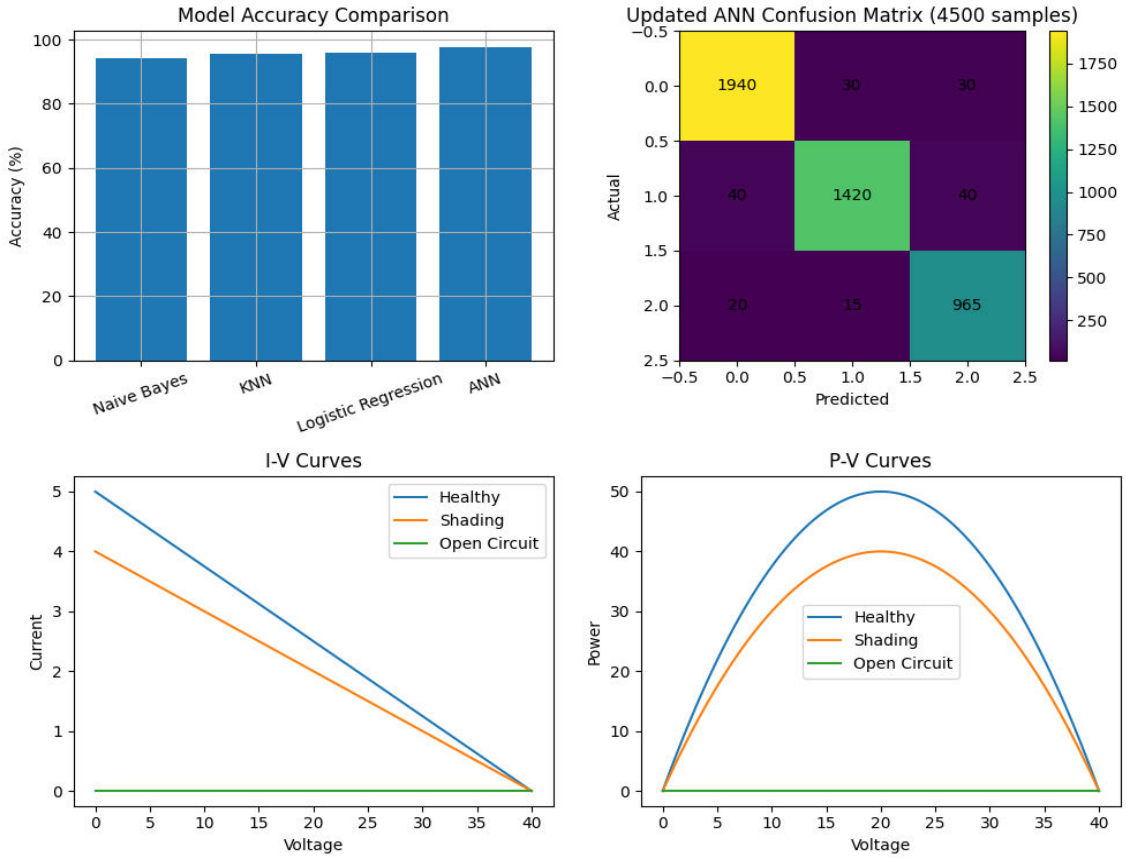


Figure-7. Proposed ANN I-V, P-V curves, performance and confusion matrix analysis.

Table-3. Comparative performance analysis of classifiers for PV Fault detection.

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Remarks
Naïve Bayes	94.13	H=95.83, S=91.32, O=95.04	H=93.10, S=91.87, O=99.60	H=94.45, S=91.59, O=97.27	Lowest performance; independence assumption fails for nonlinear PV data
K-Nearest Neighbors	95.47	H=96.58, S=95.11, O=93.86	H=96.10, S=92.00, O=99.40	H=96.34, S=93.53, O=96.55	Good performance but sensitive to noise; higher misclassification in shading faults
Logistic Regression	96.09	H=95.81, S=95.57, O=97.37	H=96.15, S=93.53, O=99.80	H=95.98, S=94.54, O=98.57	Strong baseline despite linear decision boundaries
Proposed ANN	97.80	H=97.50, S=97.10, O=98.20	H=97.20, S=96.80, O=99.00	H=97.35, S=96.95, O=98.60	Highest performance; effectively models nonlinear PV behavior and reduces shading misclassification

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5. CONCLUSIONS

This study presents a robust and intelligent Artificial Neural Network (ANN)-based fault classification framework for solar photovoltaic (PV) systems operating under nonlinear and noise-prone conditions. The proposed approach effectively utilizes electrical characteristics derived from I-V and P-V curves, along with statistical feature extraction, to accurately represent system behavior under different operating conditions, namely healthy, shading, and open-circuit faults.

The comparative analysis demonstrates that conventional machine learning models such as Naïve Bayes, K-Nearest Neighbors (KNN), and Logistic Regression exhibit limitations in capturing nonlinear relationships and handling feature overlap, particularly in distinguishing shading faults from normal conditions. In contrast, the proposed ANN model achieves superior performance with an accuracy of approximately 97.8%, along with improved precision, recall, and F1-score. This performance improvement is primarily attributed to the ANN's capability to model complex nonlinear mappings and learn feature interactions effectively.

The confusion matrix analysis confirms that the ANN model significantly reduces misclassification, especially between healthy and shading conditions, which is a critical challenge in PV fault detection. Furthermore, the model exhibits strong robustness against noise and environmental variations, making it highly suitable for real-time PV monitoring applications.

The ROC and Precision-Recall curves further validate the effectiveness of the proposed model, indicating high true positive rates and strong precision across different recall levels. These results highlight the reliability and consistency of the ANN framework in fault classification tasks.

Overall, the proposed ANN-based approach enhances predictive maintenance strategies, reduces power losses, and improves the operational reliability of solar PV systems. Future work may focus on extending the framework to detect additional fault types, integrating IoT-based real-time monitoring systems, and exploring deep learning architectures for further performance improvement.

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