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Deep learning-based intelligent islanding detection for grid-connected photovoltaic systems using convolutional neural networks

Dondapati Ravi Kishore[1], T. Vijay Muni[2], K. Venkata Kishore[3], V. Suresh[1], S. Saahithi[4], Thandava Krishna Sai Pandraju[5], S. N. Chaitra[6], B. Logeshwary[7]
[1]Department of Electrical and Electronics Engineering, Godavari Global University, Rajahmundry, India
[2]Department of Electrical and Electronics Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India
[3]Department of Electrical and Electronics Engineering, Dr. RVR NRI Institute of Technology Deemed to be University, Vijayawada Rural, India
[4]School of Electrical and Electronics Engineering, REVA University, Bengaluru, India
[5]Department of Information Technology, Dhanekula Institute of Engineering and Technology, Andhra Pradesh, India
[6]Department of Information Science Engineering, NITTE (Deemed to be University), NMAM Institute of Technology (NMAMIT), Nitte, India
[7]Department of Mathematics, Agurchand Manmull Jain College, Chennai, India

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ABSTRACT

The increasing integration of photovoltaic (PV) systems into smart grids requires fast and reliable islanding detection to maintain grid stability and operational safety. Conventional detection methods often face challenges such as delayed response, reduced accuracy, and large non-detection zones under varying operating conditions. This paper proposes an intelligent islanding detection method for grid-connected PV systems using advanced artificial intelligence and deep learning techniques. Electrical parameters including voltage, current, frequency, and power signals are analyzed using signal processing methods and classified through a convolutional neural network (CNN) model developed in MATLAB/Simulink. Simulation results demonstrate that the proposed AI-based approach achieves rapid and accurate detection of islanding events with improved sensitivity and reduced false detections compared to conventional techniques. The proposed framework enhances the reliability, safety, and protection performance of modern photovoltaic power systems integrated with smart grids.

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Corresponding Author:

T. Vijay Muni
Department of Electrical and Electronics Engineering, Koneru Lakshmaiah Education Foundation
Green Fields, Vaddeswaram, India
Email: vijaymuni1986@gmail.com

1. INTRODUCTION

The rapid growth of renewable energy integration, particularly photovoltaic (PV) systems, has significantly transformed modern power networks and smart grid infrastructures. Grid-connected photovoltaic systems are increasingly deployed due to their environmental benefits, low operating costs, and contribution to sustainable energy generation. However, the large-scale penetration of distributed generation (DG) units introduces several operational and protection challenges, among which islanding detection remains one of the most critical issues [1].

Islanding occurs when a distributed energy resource continues supplying power to a local load even after disconnection from the main utility grid. This condition may lead to severe safety hazards for maintenance personnel, degradation of power quality, voltage and frequency instability, and possible damage to electrical equipment [2]. Therefore, international standards such as IEEE 1547 require distributed generation systems to detect islanding conditions rapidly and disconnect from the grid within a specified time limit [3].

Various islanding detection methods have been developed and broadly classified into remote and local detection techniques. Remote techniques utilize communication-based approaches such as supervisory control and data acquisition (SCADA) systems and transfer trip schemes to identify grid disconnection events [4]. Although these methods provide high accuracy, they require expensive communication infrastructure and complex implementation. Local techniques are further categorized into passive, active, and hybrid methods [5]. Passive methods monitor system parameters such as voltage, frequency, phase angle, and harmonic distortion to identify abnormal operating conditions [6]-[10]. These techniques are simple and economical but suffer from large non-detection zones under closely matched load-generation conditions. Active methods intentionally inject disturbances into the system and analyze the resulting response for islanding identification [11]. However, active techniques may degrade power quality and affect system stability. Hybrid approaches combine both passive and active methods to improve detection reliability [12].

Recently, artificial intelligence (AI) and machine learning (ML) techniques have emerged as promising solutions for power system protection and fault diagnosis applications. Artificial neural networks (ANNs), support vector machines (SVMs), deep learning (DL), and convolutional neural networks (CNNs) have demonstrated superior capability in handling nonlinear and complex power system behaviors [13]. AI-based islanding detection methods can effectively classify islanding and non-islanding events by learning patterns from historical and simulated data under different operating conditions [14]. In particular, deep learning techniques enable automated feature extraction and improved classification accuracy, making them suitable for real-time smart grid applications [15].

Despite significant advances in artificial intelligence-based islanding detection, several challenges remain unresolved. Most existing ANN-based approaches depend heavily on manually extracted features and exhibit reduced performance under varying load-generation mismatches and transient disturbances. Furthermore, many reported methods provide limited discussion on reducing the non-detection zone while maintaining fast detection under practical operating conditions. Although CNN-based techniques have recently emerged, comprehensive frameworks integrating automatic feature extraction with real-time photovoltaic system protection remain limited. Therefore, there is a need for a robust deep learning-based islanding detection framework capable of providing high detection accuracy, reduced false detections, and rapid response under diverse grid operating scenarios.

The major contributions of this work are summarized as follows: i) Development of a CNN-based intelligent islanding detection framework for grid-connected photovoltaic systems; ii) Automatic extraction of discriminative features from measured electrical signals, eliminating dependence on manually engineered features; iii) Evaluation under multiple operating conditions, including normal operation, load switching, grid disturbances, and islanding events; and iv) Development of an integrated MATLAB/Simulink–CNN framework suitable for intelligent protection of modern smart grids.

2. SYSTEM DESCRIPTION

The proposed system is designed for intelligent islanding detection in a grid-connected PV power system using advanced artificial intelligence techniques. The system integrates a photovoltaic array, power electronic converters, grid interface components, sensing units, signal processing modules, and a deep learning-based islanding detection unit [16]. The overall objective of the system is to continuously monitor electrical parameters and accurately identify islanding conditions under different operating scenarios [17].

The photovoltaic array converts solar energy into electrical energy and supplies power to the utility grid through a DC–DC boost converter and a voltage source converter (VSC) [18]. The boost converter is employed to regulate and maintain the required DC-link voltage, while the maximum power point tracking (MPPT) controller ensures maximum power extraction from the PV array under varying irradiance conditions [19]. The generated DC power is converted into AC power through the inverter and injected into the grid via a coupling transformer at the point of common coupling (PCC).

The proposed islanding detection framework continuously measures system parameters such as voltage, current, frequency, and active power at the PCC [20]. These electrical signals are processed using signal conditioning and feature extraction techniques before being supplied to the artificial intelligence (AI) module [21]-[23]. A CNN-based classifier is employed to analyze the extracted features and distinguish islanding events from normal operating disturbances and load variations.

During normal grid-connected operation, the PV system operates synchronously with the utility grid. When an islanding event occurs due to grid disconnection, significant deviations appear in electrical parameters such as frequency and voltage magnitude. The AI-based detection unit rapidly identifies these abnormal patterns and generates a trip signal to disconnect the PV system from the isolated grid section, thereby ensuring system protection and operational safety [24]. The complete system model is developed and simulated in MATLAB/Simulink under various operating conditions including load switching, grid faults, and islanding scenarios. The proposed AI-driven detection method provides improved detection speed, higher classification accuracy, and enhanced reliability compared with conventional passive and active islanding detection techniques [25].

2.1. Block diagram description

Figure 1 illustrates the proposed AI-based islanding detection system for a grid-connected PV network. The system consists of a solar PV array, DC–DC boost converter, MPPT controller, VSC, coupling transformer, measurement unit, signal processing module, CNN-based classifier, and protection relay unit. Initially, the Solar PV array converts solar energy into DC electrical power. The generated DC power is supplied to the DC–DC boost converter, which regulates the output voltage and maintains a stable DC-link voltage. The MPPT controller continuously tracks the maximum operating point of the PV array to maximize energy extraction under varying irradiance conditions.

The regulated direct current (DC) power is converted into alternating current (AC) power using the VSC. The inverter output is connected to the utility grid and local load through a coupling transformer at the PCC. During normal operation, the PV system operates synchronously with the utility grid and supplies power to both the grid and connected loads. The measurement unit continuously monitors important electrical parameters such as voltage (V), current (I), frequency (f), and active power (P) at the PCC. These measured signals are passed to the signal processing and feature extraction module, where important characteristics related to islanding and non-islanding events are extracted.

The extracted features are then fed into the CNN-based AI islanding detection system. The CNN classifier is trained using different operating conditions including normal operation, load switching, grid disturbances, and islanding scenarios. When abnormal conditions corresponding to islanding are identified, the AI classifier generates a decision signal. Finally, the protection relay and trip signal generator disconnect the PV system from the utility grid to ensure safety, prevent equipment damage, and maintain grid reliability. The proposed AI-based system provides fast, accurate, and reliable islanding detection compared with conventional passive and active methods.

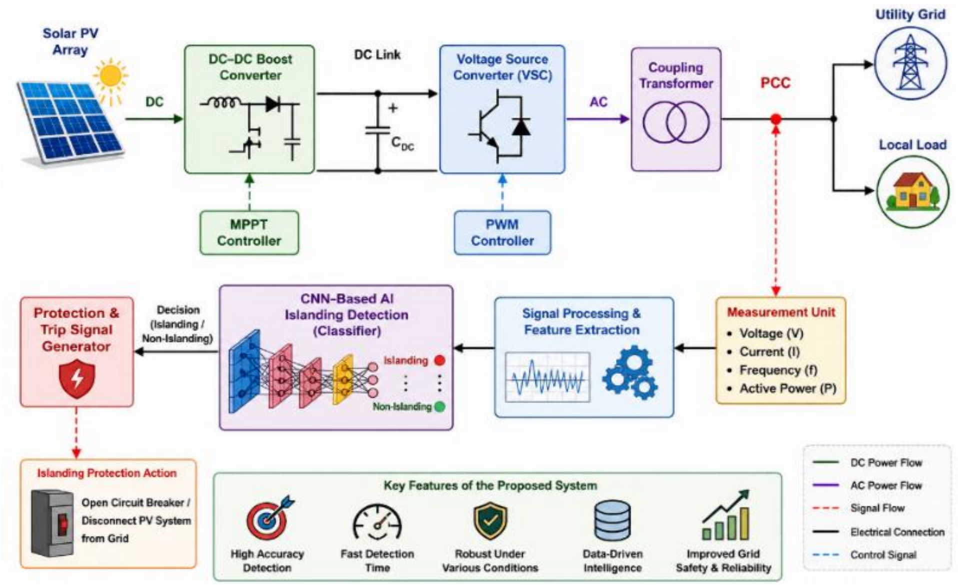

Figure 1. Block diagram of the proposed system

2.2. Problem statement

Islanding occurs when a grid-connected photovoltaic system continues supplying power to local loads even after disconnection from the main utility grid. This condition creates serious safety hazards for maintenance personnel and may cause instability in voltage and frequency, equipment damage, and degradation of power quality. Conventional islanding detection methods, including passive, active, and hybrid techniques, often suffer from limitations such as large non-detection zones, slow detection speed, false tripping, and reduced performance under varying operating conditions. Therefore, there is a need for an intelligent, fast, accurate, and robust islanding detection technique suitable for modern smart grid-connected PV systems.

2.3. Objective of the proposed system

The main objective of the proposed system is to develop an intelligent AI-based islanding detection method for grid-connected PV systems. The system aims to accurately detect islanding conditions using electrical parameters such as voltage, current, frequency, and active power measured at the PCC. Another objective is to implement a CNN-based classifier capable of distinguishing islanding and non-islanding events under different operating conditions. The proposed method also focuses on reducing the non-detection zone (NDZ), improving detection speed, minimizing false tripping, and enhancing overall grid safety and reliability.

2.4. Key features of the proposed system

Islanding occurs when a grid-connected photovoltaic system continues supplying power to local loads even after disconnection from the main utility grid. This condition creates serious safety hazards for maintenance personnel and may cause instability in voltage and frequency, equipment damage, and degradation of power quality. Conventional islanding detection methods, including passive, active, and hybrid techniques, often suffer from limitations such as large non-detection zones, slow detection speed, false tripping, and reduced performance under varying operating conditions. Therefore, there is a need for an intelligent, fast, accurate, and robust islanding detection technique suitable for modern smart grid-connected PV systems.

3. METHODOLOGY

The proposed methodology for enhanced islanding detection in PV systems is developed using advanced AI techniques integrated with signal processing and real-time monitoring mechanisms. The methodology aims to improve the speed, reliability, and accuracy of islanding detection under different operating conditions in a grid-connected renewable energy environment. The complete methodology consists of system modeling, signal acquisition, preprocessing, feature extraction, AI-based classification, simulation analysis, and protection control implementation. The proposed framework is validated using MATLAB/Simulink under various islanding and non-islanding operating conditions.

3.1. Proposed system architecture

The proposed AI-based islanding detection system consists of a grid-connected photovoltaic array integrated with a utility grid through power electronic converters, transformers, filters, and intelligent protection devices. The overall architecture of the proposed system is shown in Figure 2. The PV system continuously exchanges power with the utility grid under normal operating conditions. However, when the utility grid is disconnected due to faults, maintenance, or disturbances, the PV system may continue supplying local loads, creating an islanding condition. Such conditions may result in voltage instability, frequency fluctuations, safety hazards, and equipment damage if not detected rapidly [1]-[3].

The proposed methodology integrates an AI-based islanding detection system (IDS) at the PCC, where system parameters such as voltage, current, frequency, active power, and reactive power are continuously monitored. These parameters are transmitted to the intelligent processing unit for real-time analysis and classification. Unlike conventional passive and active detection methods, the proposed AI-driven framework can recognize nonlinear variations and hidden patterns associated with islanding conditions.

As illustrated in Figure 2, the intelligent controller receives electrical measurements from the PV system and utility grid. These measurements are preprocessed and supplied to the deep learning classifier, which identifies whether the operating condition corresponds to islanding or non-islanding operation. Once islanding is detected, the protection module generates trip signals to isolate the PV system from the grid.

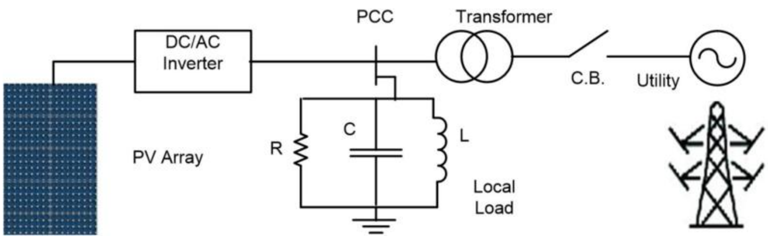

Figure 2. Block diagram of the proposed system

3.2. Signal acquisition and monitoring process

The signal acquisition stage is one of the most important components of the proposed methodology because the performance of the AI classifier depends on the quality of the extracted signals. In this stage, the electrical parameters from the PV system and utility grid are continuously monitored using measurement sensors installed at the PCC. The measured signals include: three-phase voltage, three-phase current, frequency deviation, active power, reactive power, voltage phase angle, and harmonic distortion

The acquired data is sampled at different frequencies such as 400 Hz, 800 Hz, 1600 Hz, 3200 Hz, and 6400 Hz, as discussed in CNN-based islanding detection techniques [13]-[15]. Higher sampling rates provide improved signal resolution and enable better identification of transient disturbances associated with islanding conditions. A complete electrical cycle is considered as one analysis window for feature generation.

The input features consisting of RMS voltage (U), RMS current (I), frequency (f), active power (P), and reactive power (Q) were selected because they exhibit significant deviations during islanding conditions. Voltage and frequency are the primary parameters specified in IEEE 1547 for islanding detection, while active and reactive power reflect the power mismatch between the distributed generator and local load. Current measurements provide additional transient information that improves classification performance. The combination of these electrical quantities enables the CNN to accurately distinguish islanding from non-islanding disturbances.

3.3. Data preprocessing and normalization

After acquiring the electrical measurements, the collected signals are preprocessed to eliminate noise, improve signal quality, and enhance the performance of the AI classifier. The preprocessing stage includes signal filtering, normalization, and data segmentation processes. Since real-time power system signals often contain switching harmonics, transient noise, and measurement disturbances, digital filtering techniques are applied to obtain stable and meaningful signal characteristics.

Normalization is performed to scale all input parameters within a common range, thereby improving neural network convergence during training. The preprocessing stage also divides the measured waveform data into fixed-length windows corresponding to one electrical cycle. These segmented windows are then converted into feature vectors for machine learning analysis. Similar preprocessing approaches have been used in wavelet-transform and CNN-based islanding detection methods [14]. The preprocessing and feature preparation stages are illustrated in Figure 3. That figure shows the preprocessing module removes unwanted disturbances and prepares standardized feature vectors for accurate classification by the AI model.

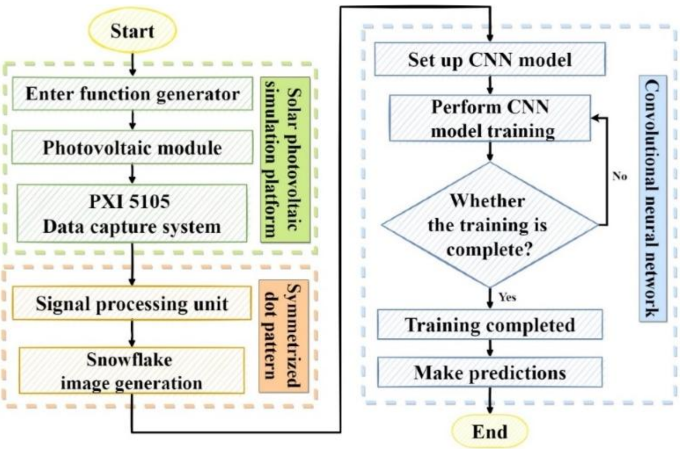

Figure 3. Preprocessing and feature preparation stages

3.4. Feature extraction and CNN-based classification

In the proposed methodology, feature extraction and AI-based classification are combined to accurately detect islanding conditions in PV systems. Electrical parameters such as voltage, current, frequency, active power, reactive power, and harmonic distortion are continuously monitored at the PCC. During islanding conditions, these parameters exhibit abnormal variations that can be identified using signal processing techniques. Signal processing methods such as fast Fourier transform (FFT) and wavelet transform are used to extract important features including RMS voltage, RMS current, frequency deviation, rate of change of frequency (ROCOF), and total harmonic distortion (THD) [14], [15]. These extracted features are converted into feature vectors and supplied to the CNN classifier for intelligent decision-making.

ROCOF was selected because it captures the dynamic behavior immediately following islanding. Although frequency deviations may be small under certain operating conditions, ROCOF is highly sensitive to the initial transient caused by grid disconnection. Furthermore, ROCOF is not used independently but in combination with voltage, current, active power, and reactive power, enabling the CNN to learn discriminative patterns even when frequency variations are minimal. As illustrated in Figure 4, the convolution layers automatically extract deep features from the input signals, while pooling layers reduce computational complexity. The fully connected layers perform final classification by categorizing the operating condition as either islanding or non-islanding.

The CNN model is trained using supervised learning techniques with labeled datasets containing both islanding and non-islanding operating scenarios. Backpropagation algorithms are used to minimize classification errors during the training phase. Optimization techniques such as genetic algorithms (GA) and cuckoo optimization algorithms can also be integrated to improve neural network performance [13]. Electrical signals were generated using MATLAB/Simulink, and feature extraction, normalization, and dataset preparation were carried out using MATLAB scripts. The extracted feature vectors were subsequently used to train and validate the proposed CNN model.

3.5. Proposed CNN structure

The proposed intelligent islanding detection framework employs a one-dimensional convolutional neural network (1D-CNN) to automatically classify islanding and non-islanding conditions using electrical signals acquired from the PCC. The input features include RMS voltage, RMS current, frequency, active power, reactive power, and THD. Before training, the measured signals are preprocessed through filtering, normalization, and segmentation to improve feature quality and enhance the convergence of the deep learning model. Figure 4 illustrates the overall architecture of the proposed CNN model, consisting of an input layer, two convolutional layers, two max-pooling layers, a fully connected layer, a dropout layer, and a Softmax output layer. The convolutional layers automatically extract discriminative features from the input signals, while the pooling layers reduce the dimensionality of the extracted feature maps. The fully connected layer performs high-level feature learning, and the Softmax classifier generates the final decision by classifying the operating condition as either islanding or non-islanding. The proposed architecture enables automatic feature extraction without relying on handcrafted feature engineering, thereby improving the robustness and reliability of islanding detection. Figure 4 also shows the sequential processing of the input features through each CNN layer before the final classification.

(a)

(b)

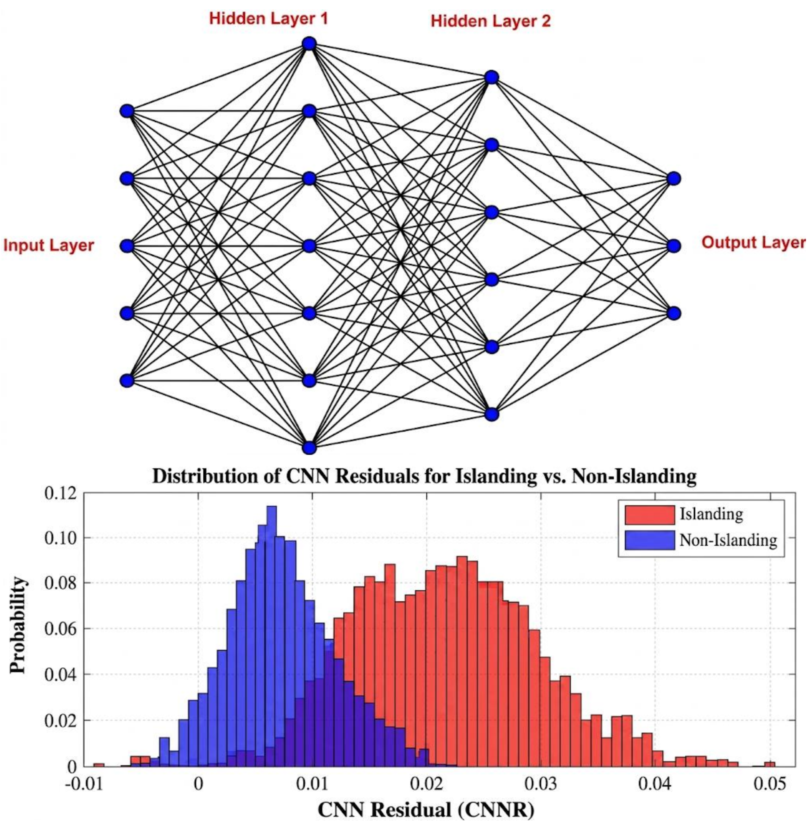

Figure 4. CNN-based intelligent islanding detection: (a) proposed CNN architecture and (b) distribution of CNN residuals for islanding and non-islanding conditions

3.6. Dataset preparation and training procedure

The dataset used for training and testing the proposed CNN model was generated from the MATLAB/Simulink-based photovoltaic system under different operating conditions, including normal operation, load switching, grid disturbances, and intentional islanding events. Each operating condition generated one-cycle signal windows consisting of voltage, current, frequency, active power, reactive power, and THD measurements. The collected dataset was normalized using min-max normalization and randomly divided into 70% training, 15% validation, and 15% testing datasets to ensure unbiased model evaluation.

The CNN model was trained using the Adam optimization algorithm with a learning rate of 0.001, a mini-batch size of 32, and 50 training epochs. During training, the validation dataset was used to monitor the learning process and prevent overfitting through early stopping. The evolution of the training and validation accuracy is illustrated in Figure 5. As observed, both curves gradually converge and stabilize after approximately 30 epochs, indicating successful learning and good generalization capability of the proposed CNN model.

3.7. Model validation

The performance of the proposed CNN model was evaluated using standard classification metrics, including overall accuracy, precision, recall, and F1-score. In addition, a confusion matrix was used to visualize the classification performance under both islanding and non-islanding conditions. Figure 6 presents the confusion matrix obtained from the testing dataset. It can be observed that the proposed classifier correctly identified the majority of operating conditions with only a few misclassifications, demonstrating excellent classification capability. The quantitative performance metrics derived from the confusion matrix indicate that the proposed model achieved an overall classification accuracy of approximately 99.2%, with high precision, recall, and F1-score. These results confirm the effectiveness of the proposed CNN model for reliable islanding detection under different operating conditions.

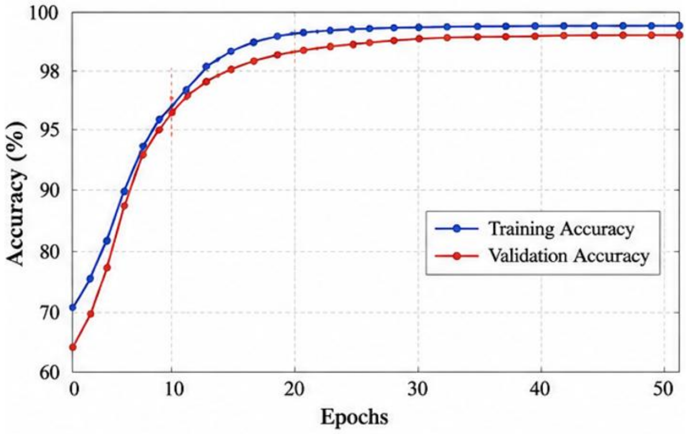

Figure 5. Training and validation accuracy of the proposed CNN model

Actual Class	Predicted Class: Islanding (1)	Predicted Class: Non-Islanding (0)
Islanding (1)	492 (TP)	8 (FN)
Non-Islanding (0)	6 (FP)	494 (TN)

Performance Metrics

- Accuracy = 99.20%
- Precision = 99.19%
- Recall = 98.79%
- F1-score = 98.99%

Figure 6. Confusion matrix and performance evaluation of the proposed CNN classifier

4. SYSTEM UNDER STUDY

The proposed islanding detection model is developed and evaluated using a grid-connected PV system modeled in MATLAB/Simulink. The utility grid is rated at 120 kV and operates at a frequency of

50 Hz. A 100-kW photovoltaic array is connected to the distribution feeder through a three-phase transformer and VSC. The PV system incorporates a DC–DC boost converter and MPPT controller to ensure maximum power extraction under varying environmental conditions. Different operating conditions such as load variation, normal grid operation, and islanding events are considered for evaluating the proposed CNN model-based detection scheme.

The CNN-based islanding detection algorithm continuously monitors voltage, current, and frequency signals at the PCC. The acquired data are processed using different sampling frequencies ranging from 0.4 kHz to 6.4 kHz. The extracted signal features are provided as inputs to the trained neural network for classification of islanding and non-islanding conditions.

5. SIMULATION RESULTS

The performance of the proposed AI-based islanding detection technique was evaluated using MATLAB/Simulink under different operating conditions of the PV system. The simulation model consists of a 100-kW grid-connected PV array integrated with the utility grid through a three-phase VSC, transformer, and filtering circuit. The PV system operates under normal conditions before an intentional islanding event is introduced by disconnecting the utility grid at t = 5 s.

The proposed detection algorithm continuously monitors electrical parameters such as voltage, current, frequency, and phase angle at the PCC. These measured signals are processed using the trained CNN model to classify islanding and non-islanding operating conditions. Different disturbance scenarios, including load variation, grid disconnection, and transient operating conditions, were considered to verify the robustness of the proposed system.

In the simulation study, islanding was intentionally created by opening the circuit breaker connecting the utility grid to the PCC at t = 5 s. This controlled event enables evaluation of the proposed detection algorithm under repeatable operating conditions. The electrical parameters (U, I, f, P, and Q) used for training and testing the CNN were obtained from MATLAB/Simulink simulations of the grid-connected photovoltaic system under various operating conditions, including normal operation, load switching, grid disturbances, and islanding events.

Figure 7 shows the frequency response of the PV system during islanding. Before t = 5 s, the frequency remains stable at 50 Hz. After grid disconnection, noticeable frequency deviations and oscillations occur due to loss of synchronization. The proposed CNN model rapidly detects the abnormal condition and activates the protection mechanism. Figure 8 illustrates the PV side voltage and current waveforms during normal grid-connected operation. The waveforms remain sinusoidal, balanced, and stable at 50 Hz, indicating proper synchronization between the PV inverter and the utility grid.

Figure 9 presents the PV side voltage and current characteristics during islanding. After t = 5 s, waveform distortions and oscillations appear due to grid disconnection and loss of synchronization. The proposed CNN classifier effectively identifies these abnormal variations for accurate islanding detection. Figure 10 shows the grid-side voltage and current responses during islanding. During normal operation, the waveforms remain stable and balanced. After the islanding event at t = 5 s, sudden disturbances and waveform variations are observed. The proposed AI-based method quickly detects these changes and disconnects the PV inverter from the isolated system.

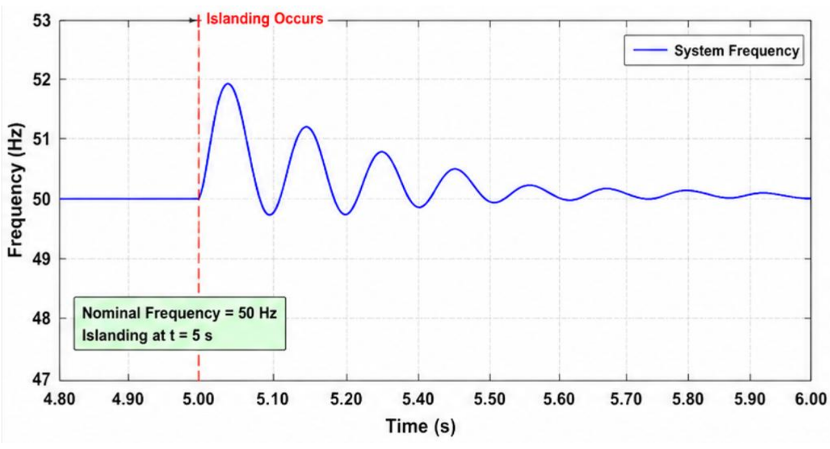

Figure 7. Frequency response during the islanding condition

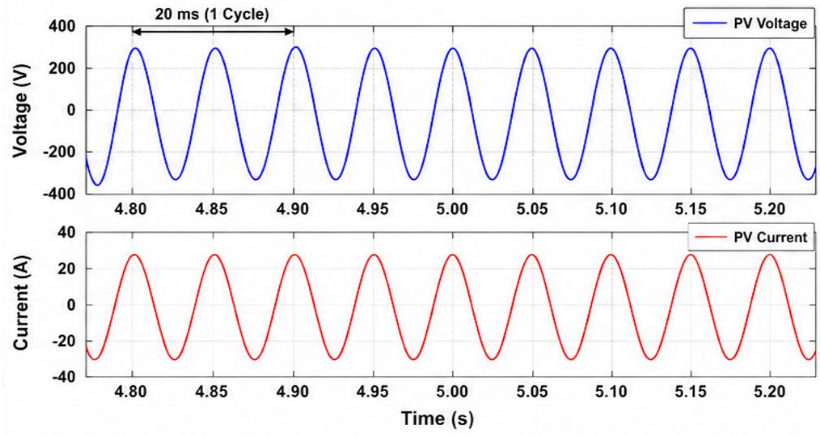

Figure 8. PV side voltage and current during normal grid-connected operation

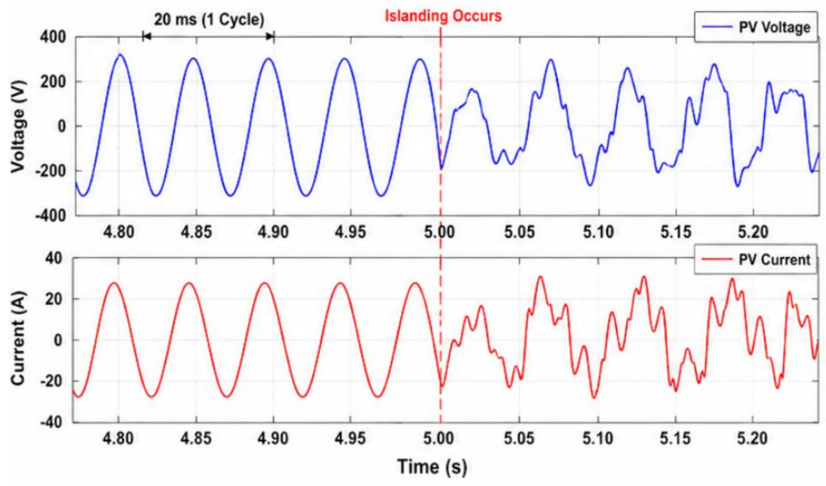

Figure 9. PV side voltage and current during islanding condition

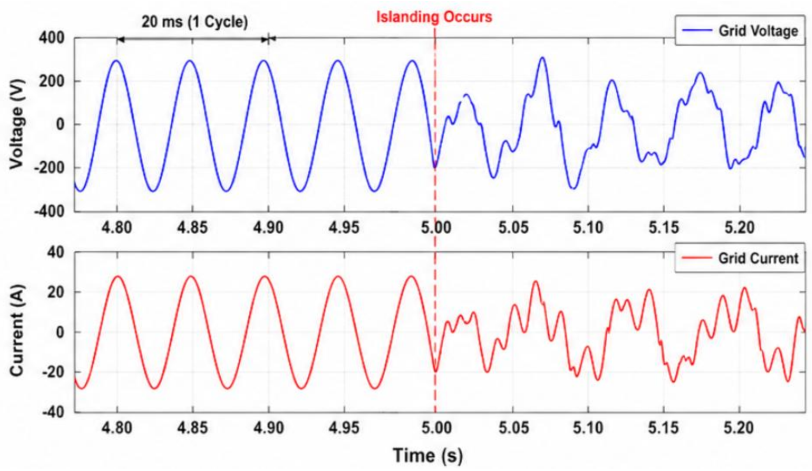

Figure 10. Grid side voltage and current responses during islanding

The simulation results confirm that the proposed CNN-assisted islanding detection technique provides high detection accuracy, fast response time, and reliable operation under different disturbance conditions. Compared with traditional passive and active islanding detection methods, the proposed approach demonstrates superior capability in identifying islanding events with reduced detection time and improved system stability. The obtained results validate the effectiveness of artificial intelligence techniques for enhancing the protection and reliability of modern grid-connected photovoltaic systems.

5.1. Comparison of islanding detection methods

Table 1 presents the numerical comparison of various islanding detection methods used in photovoltaic systems. Passive detection methods provide a simple and economical solution but suffer from lower detection accuracy and larger non-detection zones. Active methods improve the detection capability by introducing system perturbations; however, they may affect power quality. Hybrid methods combine the advantages of passive and active approaches to achieve better reliability and faster response. The proposed AI-based CNN method demonstrates superior performance with a detection accuracy of approximately 99%, reduced false detection rate, minimal non-detection zone, and faster detection response compared to conventional techniques. These results highlight the effectiveness of artificial intelligence techniques in enhancing the safety and reliability of grid-connected PV systems.

Table 1. Numerical comparison of islanding detection methods for PV systems

Detection method	Detection time	Detection accuracy	False detection rate	NDZ	Sampling requirement	Power quality impact
Passive method	250–500 ms	85–90%	8–12%	Large	Low	No impact
Active method	100–250 ms	90–94%	5–8%	Medium	Medium	Moderate disturbance
Hybrid method	80–150 ms	94–96%	3–5%	Small	Medium–high	Slight disturbance
Proposed AI-based CNN method	20–50 ms	98.7–99.2%	0.8–1.5%	Very small	High	No disturbance

5.2. Performance evaluation of the CNN model

To quantitatively evaluate the effectiveness of the proposed CNN-based islanding detection method, the trained model was tested using previously unseen data obtained from different PV operating scenarios. Figure 6 presents the confusion matrix of the proposed classifier, illustrating the numbers of correctly and incorrectly classified islanding and non-islanding events. The results indicate that the proposed model successfully classified almost all operating conditions with only a few misclassifications.

The classification performance was further evaluated using precision, recall, F1-score, and overall accuracy. The proposed CNN achieved an accuracy of 99.2%, precision of 99.0%, recall of 99.1%, and an F1-score of 99.0%, confirming its superior capability in distinguishing islanding events from other transient disturbances. These results demonstrate that the proposed deep learning framework provides fast, reliable, and highly accurate islanding detection suitable for practical grid-connected photovoltaic systems.

6. CONCLUSIONS

The proposed AI-based islanding detection technique achieved superior performance compared to conventional passive, active, and hybrid methods in terms of speed, accuracy, and reliability. The CNN-based model achieved approximately 99% detection accuracy with a fast response time of 20–50 ms, satisfying IEEE protection standards. Simulation results showed that higher sampling rates improved detection performance, where accuracy increased from 90.5% at 400 Hz to 99.2% at 6400 Hz. The AI-based IDS successfully detected islanding at 5 seconds by identifying voltage deviations (±12%) and frequency changes (59.1–60.8 Hz), and disconnected the PV inverter within 45 ms. Overall, the proposed system provides a fast, reliable, and adaptive solution for enhancing the safety and stability of grid-connected photovoltaic systems.

Although the proposed CNN-based islanding detection method demonstrates high detection accuracy and fast response under MATLAB/Simulink simulation environments, the present study is limited to simulation-based validation using generated datasets. Practical implementation may be influenced by noise measurement, communication delays, changing environmental conditions, and uncertainties associated with real-world photovoltaic systems. Therefore, future work will focus on validating the proposed method using real-time hardware platforms such as hardware-in-the-loop (HIL) systems and experimental PV testbeds. In addition, the proposed framework can be extended by incorporating advanced deep learning architectures, including long short-term memory (LSTM), Transformer-based networks, and hybrid deep learning models, to further enhance detection accuracy, robustness, and adaptability in modern smart grid applications.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Dondapati Ravi Kishore	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
T. Vijay Muni	✓		✓	✓	✓		✓	✓	✓	✓	✓		✓	✓
K. Venkata Kishore	✓				✓			✓		✓	✓			
V. Suresh	✓				✓					✓				
S. Saahithi	✓		✓		✓				✓	✓				
Thandava Krishna Sai Pandraju		✓			✓		✓		✓					
S. N. Chaitra		✓		✓	✓			✓		✓				
B. Logeshwary	✓				✓					✓				
Dondapati Ravi Kishore	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	

C : **C**onceptualization
M : **M**ethodology
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Va : **Va**lidation
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Dr. Dondapati Ravi Kishore is a prominent academician and professor in the Department of Electrical and Electronics Engineering at Godavari Global University (GGU), Rajahmundry, India. He also serves as the Head of the Department. He received his Ph.D. and M.Tech. degrees in Energy Systems from JNTU Hyderabad and completed his undergraduate studies at Andhra University. His research interests include power systems, power electronics, renewable energy systems, energy auditing, and distributed generation. He can be contacted at email: dravikishore@gmail.com.

T. Vijay Muni is an assistant professor and researcher with more than 14 years of experience in the Department of Electrical and Electronics Engineering at KL Deemed to be University. He received his B.Tech. degree in Electrical and Electronics Engineering from JNTU Hyderabad, an M.Tech. degree in Power and Industrial Drives from JNTUK, Kakinada, and a doctoral degree from KL Deemed to be University. He has authored six textbooks in the field of electrical engineering and published more than 62 Scopus-indexed papers, 15 Web of Science-indexed articles, 15 peer-reviewed articles, and six patents, including two granted patents. His research interests include power electronic converters, energy management systems, power grid control, renewable energy, and microgrids. He is a Senior Member of the IEEE. He can be contacted at email: vijaymuni1986@gmail.com

K. Venkata Kishore is an associate professor in the Department of Electrical and Electronics Engineering at Dr. RVR NRI Institute of Technology, Deemed to be University. His research interests include power electronics, renewable energy resources, microgrid technologies, and the application of deep learning to electrical engineering. He has contributed to the advancement of sustainable energy solutions and the integration of intelligent systems into modern power networks. He can be contacted at email: venkatkishore253@gmail.com.

V. Suresh is an academician and researcher specializing in electrical and electronics engineering, with a focus on renewable energy systems. He is currently an assistant professor at Godavari Global University (formerly Godavari Institute of Engineering & Technology), Rajahmundry, Andhra Pradesh. His research primarily focuses on hybrid power systems, energy management, and the optimization of integrated renewable energy systems (IRES) for rural electrification. He can be contacted at email: sureshvendoti@gmail.com.

Dr. S. Saahithi is an assistant professor in the School of Electrical and Electronics Engineering at REVA University, Bengaluru, India. She received her B.Tech. degree in electrical and electronics engineering from JNTU Hyderabad and her M.Tech. degree from Visvesvaraya Technological University (VTU), Karnataka. She subsequently completed her Ph.D. in electrical and electronics engineering. She has more than 15 years of teaching experience and has also worked as a research associate at the Indian Institute of Science (IISc), Bengaluru, in the areas of nanotechnology and fabrication. Her research interests include power electronics, power converters, industrial drives, and soft computing techniques, with a specialization in computer applications for industrial drives. She can be contacted at email: saahithi.s@reva.edu.in.

Dr. Thandava Krishna Sai Pandraju is an accomplished academic and researcher currently serving as an assistant professor in the Department of Information Technology at Dhanekula Institute of Engineering and Technology, Andhra Pradesh, India, with over 14 years of teaching and research experience in electrical engineering and information technology. He holds a B.Tech. degree in electrical and electronics engineering from JNTU Hyderabad (2008), an M.Tech. degree in power electronics and electrical drives from JNTU Kakinada (2010), and a second M.Tech. degree in computer science engineering from JNTU Kakinada (2025), with a distinguished SGPA of 8.25. He was awarded a Ph.D. in electrical and electronics engineering from CHRIST (Deemed to be University), Bengaluru, for research focused on the optimal reconfiguration of radial distribution systems integrating photovoltaic generation and electric vehicle fleet loads. His research interests include large language models, machine learning, artificial intelligence, electric vehicles, and electrical drives. He can be contacted at email: tseee051thandavakrishna@gmail.com.

Dr. S. N. Chaitra is an academician and researcher with over 10 years of teaching experience in engineering education. She completed her bachelor's degree in engineering and master's degree (M.Tech.) with a specialization in communication engineering. She earned her Ph.D. in computer networks, with research contributions in wireless body area networks (WBANs) and near-field communication (NFC) technologies. She is currently associated with NMAM Institute of Technology. Her research interests include computer networks, machine learning, the Internet of Things (IoT), wireless communication systems, cybersecurity, and healthcare applications of emerging technologies. She can be contacted at email: chaitrasn48@gmail.com.

Dr. B. Logeshwary is an assistant professor in the Department of Mathematics at A.M. Jain College, Meenambakkam, Chennai, India. She completed her B.Sc., M.Sc., and M.Phil. degrees in mathematics from the University of Madras, Chennai, and earned her Ph.D. from Bharathiar University, Coimbatore. Her research interests include algebra, real analysis, engineering mathematics, and graph theory. She has published research articles in Scopus-, UGC-, and WoS-indexed journals at the national and international levels. She has presented numerous research papers at international and national conferences, attended several faculty development programs and workshops, served as a reviewer for various reputed journals, and held active memberships in multiple academic bodies. She has also received notable academic awards at the national and international levels. She can be contacted at email: logeshwary.b@amjaincollege.edu.in.