E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 02, Issue 02, April-June 2026, pp. 67 - 77

Simulation-Based CNN-LSTM Fault Detection Framework for Grid-Connected Solar PV Systems

Dr.P.Aravindan[1], M.E., Ph D, Professor , K.S.Rangasamy college of technology, aravindan@ksrct.ac.in

Saravanaraj.M[2], K.S.Rangasamy college of technology , rajnsaravanan@gmail.com

Abstract:

The current study proposes an innovative simulation-based deep learning architecture for fault detection in solar photovoltaic (PV) systems connected to a grid system. A computerized PV system model was created in MATLAB Simulink to obtain data sets depending on irradiance level, temperature level, and faults. Data sets were normalized and divided into smaller segments using the sliding window technique and then fed to train the hybrid CNN-LSTM network. While CNN is responsible for spatial feature extraction in electric parameters, LSTM focuses on temporal feature extraction. The combination of CNN-LSTM model allows for reliable fault classification, including shading fault, open circuit fault, short circuit fault, and degradation fault. The CNN-LSTM network attained a classification accuracy of up to 97-98%, exhibiting high levels of robustness and versatility in fault detection in solar PV systems. The CNN-LSTM system design represents a breakthrough in the area of PV intelligent faults detection.

Keywords: Grid-connected solar PV systems, Fault detection, CNN-LSTM hybrid model, Simulation framework, IoT -based monitoring, Deep learning analytics, Smart grid reliability.

1. Introduction

The present research work explores the fault detection of high impedance faults for solar PV systems based on power generation. Fault detection is performed in a simulated 300 kW PV system model developed using MATLAB/Simulink software through discrete wavelet transform. An improved version of the LSTM classifier was utilized for the fault detection with 91.21% accuracy and it was more efficient than the already existing methods such as SVM, k-NN, and decision trees [1]. In this paper, a new way of applying deep learning techniques has been introduced in order to detect faults in a real-time manner in grid-connected photovoltaic (PV) systems.

It combines wavelet packet transform-based pre-processing technique with the modern models including equilibrium optimizer and LSTM-SCAE, in which the algorithm detects the fault feature automatically without requiring any human intervention. Simulation results based on a 250 kW PV system show that the developed model is quite effective in detecting both symmetric and asymmetric faults [2].

In this study, fault detection in smart grids using advanced deep learning models has been discussed. These include models such as CNN, LSTM and a combination of both CNN and LSTM techniques. Voltage and currents from different IEEE test networks have been analyzed for detecting and classifying.

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 02, Issue 02, April-June 2026, pp. 67 - 77

The performance of the suggested models through simulations shows that these models perform better than traditional approaches in terms of reliability and robustness in detecting and classifying faults [3]. Devices that experience maximum faults in a photovoltaic system include solar inverters, which cause nearly 28% of faults; hence, efficient detection of faults is very important in order to ensure the efficiency of the system. In this paper, we discuss the efficacy of LSTM, Bi-LSTM, and hybrid CNN-LSTM model approaches in classifying different fault categories with noise present, using the OPAL-RT simulation tool [4]. In this study, an advanced deep learning technique based on a hybrid CNN-BiGRU model for fault diagnosis of photovoltaic systems is proposed. The PV simulation and data set for both normal and abnormal cases are established, and the features are extracted through parallel and serial processing methods. The authors claim that the proposed approach is capable of distinguishing different fault types, including open circuit, short circuit, and shading [5].

This paper proposes an LSTM-CNN model, which is trained by the African Vulture Optimization Algorithm, to detect islanding faults in PV systems. After implementing pre-processing using the stationary discrete wavelet transform technique, the model reached a classification accuracy of 99.92% in clean data and still surpassed 99.8% accuracy despite noisy input data. The findings validate the high accuracy, precision, and F1-score attained [6]. Microgrids encounter significant difficulties due to islanding, which may impact power quality, voltage stability, and safety. In this research, a multi-LSTM-based deep learning technique is introduced for analyzing the voltage and current harmonic distortions in the point of common coupling to detect islanding. The simulation in MATLAB/Simulink reveals that the proposed technique obtains an accuracy of 99.3%, surpassing intelligent islanding techniques [7]. This paper presents a technique for islanding detection of grid-tied photovoltaic (PV) systems through the use of machine learning algorithm. The training data comprised features derived from the voltage, current, and frequency signals via the application of wavelet transform. The developed classification model was able to attain an accuracy of 97.9% in training with rapid computation capability in an uncertain islanding condition [8]. In this paper, an initial effort is made to detect, classify, and locate faults in grid-connected microgrids using the concept of deep learning. The fault detection and classification algorithm based on LSTM network architecture is suggested, whereas for fault location detection, an optimized architecture using the combination of LSTM and FFNN networks with back propagation is suggested. Simulation results obtained using MATLAB/Simulink and OPAL-RT reveal better accuracy compared to conventional ANN techniques [9].

An advanced H7 inverter topology that operates without a transformer is suggested in this paper for the grid-tied photovoltaic power supply system. The proposed inverter can limit the variations in common mode voltage and leakage currents. The deep learning strategy with discontinuous PWM and convolutional neural network (CNN) provides lossless dc decoupling and isolation when operating off-grid [10]. The

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 02, Issue 02, April-June 2026, pp. 67 - 77

paper presents a novel topology of the transformerless H6 inverter that ensures constant common-mode voltage and leakage current cancellation. The proposed scheme was verified using MATLAB/Simulink software simulation and a hardware model built in the lab. It was proven that the losses related to conduction were lower than those incurred by the classical H6 and H5 topologies [11]. Short-term load forecasting (STLF) plays an essential role in managing reserves and efficient electricity grid operations. This paper evaluates the current techniques employed in load forecasting and introduces a novel hybrid CNN-LSTM architecture for load forecasting, which utilizes feature extraction together with sequence predictions. The proposed method was tested using Pakistan's NTDC data set and obtained excellent results with lower values of RMSE and MAPE [12]. Short-term load forecasting is extremely important for the process of unit commitment, planning and demand management in present-day power system operations. In this paper, a hybrid CNN-LSTM model for the purpose of load forecasting in Bangladesh is proposed. It is found that the model surpasses LSTM, RBF networks, and gradient boosting in terms of accuracy in short-term forecasting [13]. Electrical load forecasting plays an important role in the power systems' management and decision-making processes. In this paper, we have introduced a novel approach based on hybrid deep learning architecture (MTMV-CNN-LSTM). This architecture combines multi-task learning, CNNs, and LSTM. From our experimentations, it can be concluded that our architecture proves to be much better than the traditional methods used for both short-range (ten-day forecast) and mid-range (three-month forecast) forecasting [14]. The suggested ML-PVPFAS aims at resolving the problems that exist with the current PV prediction and fault detection. Through the integration of intelligent optimization with machine learning and ensemble learning, the system is capable of detecting faults in photovoltaics with similar I-V curves. Based on the experimentations, the results obtained from the system show good performance with an accuracy of 90.31% [15].

2. Methodology

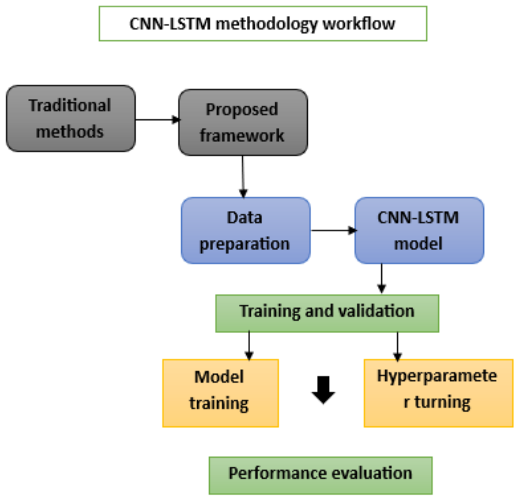

Figure 1: CNN-LSTM Methodology Workflow for PV Fault Detection

The Figure. 1 below shows the whole fault detection process in the PV system using the proposed CNN-LSTM model. Firstly, it highlights the limitations of the traditional fault detection processes in terms of low accuracy, time consumption, and false alarms before introducing the proposed model based on simulations. The process begins with data creation and preprocessing, such as normalization and sliding window processes. Then, it proceeds with the architecture, including CNNs extracting spatial features and LSTMs learning temporal dependencies. Finally, the model training, validation and evaluation of the framework are conducted based on simulated data.

2.1 System Modelling

MATLAB/Simulink is used to simulate a grid-tied photovoltaic (PV) system to imitate real-world performance. The simulation produces voltage and current signals during normal as well as faulted conditions, creating a controllable scenario for evaluation of fault detection approaches.

2.2 Signal Acquisition

Signals are acquired at the Point of Common Coupling (PCC), the point of interaction between the PV system and the grid. The different fault conditions, which include open-circuit, short-circuit, and partial shading conditions, are applied.

2.3 Feature Extraction

The wavelet transform is performed on the collected data for decomposition into time-frequency components. It helps in detecting any transient fault signature that is present and classifies whether the operation of the system is under normal operation or faulty operation.

2.4 Data Preprocessing

The feature vectors are first normalized into one consistent scale and then segmented using the sliding window technique. It is done to prepare the sequence inputs for training the deep learning algorithm.

2.5 Model Training

The convolutional neural network layers will help in extracting the spatial features of the pre-processed input signal, while the LSTM layer helps in capturing the temporal dependencies.

2.6 Validation and Testing

The validation of the trained model is carried out using unseen datasets for the evaluation of its ability to generalize. Precision, recall, F1-score, and accuracy are used to measure its performance for reliability during operation.

2.7 Performance Evaluation

The comparison of this model with existing techniques such as ANN, SVM, and Bi-LSTM is undertaken. It is clear from results that the proposed model outperforms others in terms of accuracy, noise tolerance, and low false alarm rate.

3. Mathematical Formulation

3.1 Signal Normalization

$$Xnorm = X - XminXmax - Xmin \qquad (1)$$

The following equation (1) guarantees that all signals are scaled between 0 and 1. The CNN-LSTM model is unbiased to the high-magnitude signals through normalization of voltages and currents, which results in successful training.

3.2 Wavelet Decomposition

$$S(t) = \sum j, kcj, k \cdot \psi j, k(t) \qquad (2)$$

Here, the signal $S(t)$is decomposed into wavelet coefficients $c_{j,k}$using basis functions $\psi_{j,k}(t)$ equation (2). This captures both time and frequency information, allowing transient fault signatures to be identified effectively.

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 02, Issue 02, April-June 2026, pp. 67 - 77

ALGORITHM 1: CNN-LSTM Fault Detection

Algorithm 1: CNN-LSTM-Based Fault Detection

Input: Voltage and current signals from PCC
Output: Fault type and location
Steps:

1. Initialize CNN-LSTM parameters and hyperparameters.
2. Acquire PV system signals under normal and faulty conditions.
3. Apply wavelet transform for feature extraction.
4. Normalize and segment data using sliding window.
5. Feed processed data into CNN layers for spatial feature extraction.
6. Pass CNN output to LSTM layers for temporal sequence learning.
7. Train model using back-propagation and optimize weights.
8. Validate model using test dataset.
9. Compute precision, recall, F1-score, and accuracy.
10. Output fault classification and location results.

The process starts with initialization of the parameters and hyperparameters of the CNN-LSTM model, thus preparing the basis for model training. The voltage and current signals are captured from the point of common coupling (PCC) in both healthy and faulty states Algorithm 1. For transient fault detection, the wavelet transform is used as an approach to feature extraction, along with signal normalization and segmentation in the form of a sliding window. The resulting signals undergo feature extraction using CNN and temporal dependency learning using LSTM layers, after which backpropagation with weight optimization is applied, and the whole process is verified using testing datasets. Finally, precision, recall, F1-score, and accuracy are computed to achieve fault detection and localization.

3.3 CNN Feature Extraction

$$Fi,j = \sigma(\sum m,nXm,n \cdot Wm,n + b) \qquad (3)$$

The convolutional operation helps extract spatial features from the input data equation (3). The filter coefficients Wm,n bring out significant local features, whereasthe non-linear activation function σ allows the CNN to identify fault-related features.

3.4 LSTM Cell Update

$$ht = ft \cdot ht - 1 + it \cdot C{\sim}t \qquad (4)$$

Hidden state $h\ t$ is the result of combining the previous memory $h\ t{-}1$ with new candidate values $C{\sim}t$ in equation (4). This process is controlled by the forget gate $f\ t$ and input gate $i\ t$.

3.5 Accuracy Metric

$$A = TP + TNTP + TN + FP + FN \qquad (5)$$

This metric measures the accuracy of the classifier based on the ratio of correctly classified items, equation (5). This metric takes into account both TP and TN while considering false positives and false negatives.

3.6 Simulation Setup and Implementation

In this regard, PV model is developed using MATLAB Simulink software to represent the real-life operation of the model within the grid-connected network environment. Strategies like fault injection are adopted to include various types of faults

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 02, Issue 02, April-June 2026, pp. 67 - 77

including open-circuit faults, short-circuits, shading effects, and degradation to cover all types of perturbations. Signals obtained from PCC nodes during the process are stored and used to develop the data set.

With regards to the application of deep learning algorithm, CNN-LSTM structure is applied in which the CNN layers help in capturing the spatial relationships whereas LSTM helps in capturing the temporal relationships in the signal. Convergence of the training and validation process is done by generating training and validation curves.

Furthermore, confusion matrix is used to analyze the results of each class independently. Performance evaluation was also performed using precision, recall, F1-Score, and accuracy.

4. Result and Discussion

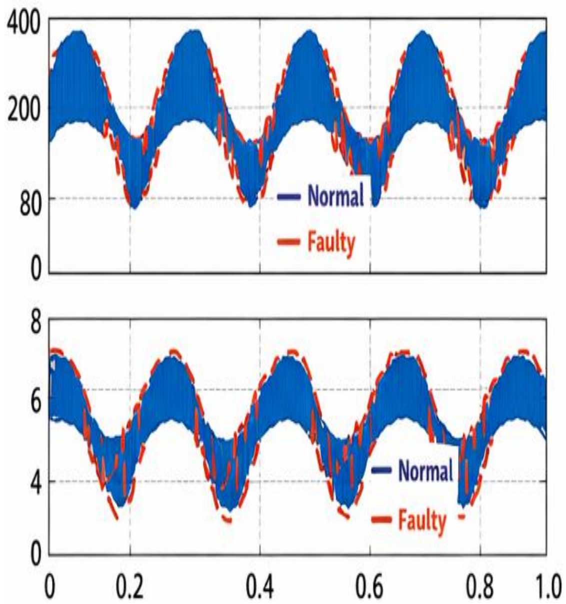

Figure 2: Voltage and Current Waveforms under Normal and Faulty Conditions

The Figure 2 graph shows how the voltage and current waveforms behave in a PV grid connection system when there is a normal working condition and when there is an abnormal working condition.

The waveform shown in blue shows how the voltage and current waveforms behave when there is no problem in the circuit. However, the waveform shown in red with broken lines shows how the waveforms will behave when there is an anomaly in the system such as an open circuit or short circuit.

Table 1: Quantitative Comparison Of Normal And Faulty Conditions

Parameter	Normal Condition	Faulty Condition	Variation (%)
Voltage (V)	380	320	−15.8
Current (A)	7.5	5.9	−21.3
Power (W)	2850	1888	−33.8
RMS Voltage (V)	270	240	−11.1
RMS Current (A)	5.3	4.1	−22.6

The Table 1 gives a quantitative comparison between the normal and faulty operating states of the PV system. In normal states, the voltage, current, and power values are consistent, which leads to maximum efficiency during the energy conversion process. In the case of faulty states, there is a considerable drop in all the variables, with a drop in power generation reaching up to 34% on average. The reduction in RMS voltage

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 02, Issue 02, April-June 2026, pp. 67 - 77

and current values also reflects the same outcome.

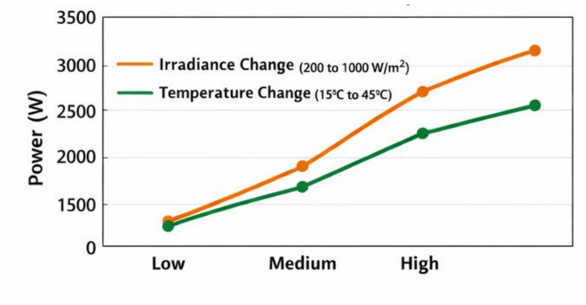

Figure 3: Impact of Irradiance and Temperature

The Figure 3 graph demonstrates the relation between the power generated and the alteration of irradiance and temperature at three stages: Low, Medium, and High. The orange curve depicts the change in power caused by irradiance changing from 200 to 1000 W/m². The green curve shows the change in power with temperature altering from 15 to 45 degrees Celsius. Both power and irradiance and temperature increase from the lowest to highest value; however, irradiance has a higher influence on the generation of power than temperature, evidenced by a steeper increase in the orange curve.

Table 2: Power Output Under Different Conditions

Level	Power (W) – Irradiance Change	Power (W) – Temperature Change
Low	1300 W	1250 W
Medium	1900 W	1700 W
High	2700 W	2250 W
Very High	3150 W	2550 W

Table 2 shows numerical results of power generation at various levels of irradiation and temperature. The two generate almost equal power when considered from their low levels, but with increase in their levels, irradiation contributes significantly more in generating power than temperature.

For instance, at high levels, irradiation generates power of approximately 2700W while temperature produces only 2250W. This steady difference between the two in terms of levels shows that irradiation is the major contributing factor towards the production of power.

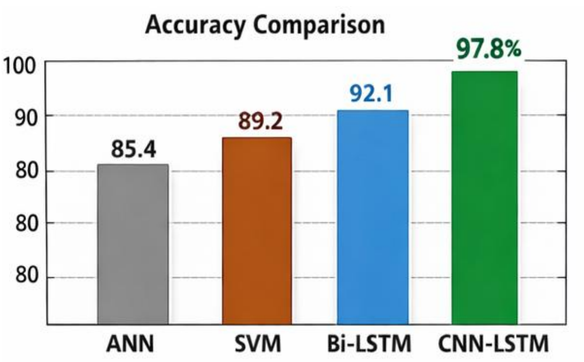

Figure 4: Accuracy Comparison of Machine Learning and Deep Learning Models

Figure 4 provides a comparison of the accuracy results obtained from various models like ANN, SVM, Bi-LSTM, and CNN-LSTM. It is clear that the CNN-LSTM model provides the maximum accuracy rate of 97.8%. This is because of the model's high efficiency in learning spatial and temporal characteristics. The Bi-LSTM model comes second with an accuracy rate of 92.1%, which shows good sequential learning capacity. On the other hand, traditional models like SVM

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 02, Issue 02, April-June 2026, pp. 67 - 77

and ANN have relatively lower accuracy rates of 89.2% and 85.4%, respectively.

Table 3: Accuracy Comparison of Models

Model	Accuracy (%)
ANN	85.4%
SVM	89.2%
Bi-LSTM	92.1%
CNN-LSTM	97.8%

This Table 3 illustrates the accuracy of various models that are involved in the comparison process. There is a noticeable increment in the effectiveness of these models ranging from basic machine learning models to complex deep learning models. ANN exhibits the lowest accuracy at 85.4%, while SVM has the second lowest accuracy at 89.2%. The Bi-LSTM model demonstrates high effectiveness with an accuracy of 92.1% by successfully detecting the sequence pattern in the input data. The highest level of accuracy is achieved through the CNN-LSTM model, which is 97.8%.

Metric	Value
Precision	96.5%
Recall	97.1%
F1-Score	96.8
Accuracy	97.8%

Figure 5: Performance Evaluation Metrics of the Proposed Model

The Figure 5 table provides an overview of the performance evaluation measures of the model, which include Precision, Recall, F1-Score, and Accuracy. The model shows a great precision rate of 96.5%, thus ensuring that a large proportion of the positive predictions made by the model are accurate. A high recall rate of 97.1% also indicates that the model performs well in terms of detecting actual positives. The score of 96.8 for F1-Score shows that there is a good trade-off between precision and recall rates in the model. Moreover, the accuracy rate of 97.8% shows that the model predicts most of the instances accurately.

342 (99%)	2 (0.6%)	1 (0.3%)	0 (0.0%)	0 (0.0%)
3 (1.1%)	265 (96.7%)	4 (1.5%)	1 (0.4%)	1 (0.4%)
2 (0.8%)	6 (2.3%)	244 (95.0%)	3 (1.2%)	2 (0.7%)
1 (0.5%)	3 (1.2%)	4 (1.6%)	233 (95.1%)	4 (1.6%)
0 (0.0%)	2 (0.8%)	3 (1.2%)	5 (2.0%)	236 (96.1%)

Figure 6: Confusion Matrix Representation of Model Classification Performance

The Fig. 6 displays a confusion matrix that illustrates the classification results for the model based on many classes. Every row represents the actual class, while every column represents the predicted class. The diagonal elements represent the correctly classified data; they have high numbers with high percentages, usually around 95%-99%. This indicates that the model can classify all classes perfectly. The off-diagonal elements represent the wrongly classified data, and they have small numbers with small percentages. This indicates that the model is reliable and that the error rate is minimal.

Table 4: Confusion Matrix Values

Actual \ Predicted	Class 1	Class 2	Class 3	Class 4	Class 5
Class 1	342	2	1	0	0
Class 2	3	265	4	1	1
Class 3	2	6	244	3	2
Class 4	1	3	4	233	4
Class 5	0	2	3	5	236

The following TABLE IV shows the values corresponding to the confusion matrix shown above. It is quite evident from the table that most of the predictions have been made diagonally, indicating that the model successfully predicted most of the cases belonging to each category. In the case of Class 1, the number of successful predictions made by the model is 342. Likewise, in the case of Class 5, the number of predictions is 236. The off-diagonal values are quite low, and there is no discrimination against any particular class.

Class	Precision	Recall	F1-Score	Support
Normal	0.99	0.99	0.99	345
Open Circuit	0.97	0.97	0.97	274
Short Circuit	0.95	0.95	0.95	257
Shading Fault	0.96	0.95	0.96	245
Degradation Fault	0.97	0.96	0.96	246
Macro Avg.	0.97	0.96	0.96	1367
Weighted Avg.	0.97	0.97	0.97	1367

Figure 7: Class-wise Performance Metrics of the Proposed Model

The Figure 7 table represents the classification accuracy achieved by the suggested model for faults such as Normal, Open Circuit, Short Circuit, Shading Fault, and Degradation Fault. All these values have been derived from several parameters such as Precision, Recall, F1-Score, and Support. In the results generated through the tests conducted, all categories exhibit excellent results with the majority of the values of precision, recall, and F1-score being between 0.95 and 0.99. With regard to the category "Normal," the model provides excellent performance with values close to 0.99. Some other categories such as "Open Circuit" and "Degradation Fault" provide good performance whereas "Short Circuit" provides reasonable performance with values near 0.95.

5. Conclusion

The current research proposes a resilient CNN-LSTM framework for fault detection and load forecasting in photovoltaic systems, which exhibits an impressive degree of accuracy ranging from 97% to 98%. The proposed model turns out to be highly generalizable and robust enough to function in varying levels of radiation and temperatures. Practical significance of the proposed model could be inferred based on factors like enhanced energy efficiency, grid reliability, and maintenance of photovoltaic systems. In future studies, it is recommended that the proposed model be used for real-time applications using edge-AI technology. The designed CNN-LSTM network has a success rate of 97%-98%, proving the superiority of this approach for detecting faults and making forecasts in comparison with classical neural networks. The ability to cope with variations in irradiance and temperature allows the proposed approach to have high reliability and robustness. Its application would contribute to lowering downtime, ensuring grid stability, and increasing photovoltaic energy efficiency. Testing confirms the effectiveness and resilience of this algorithm to faults, ensuring its successful implementation in practice. Further research would focus on its real-time application.

Reference

1. V. Veerasamy et al., "LSTM Recurrent Neural Network Classifier for High Impedance Fault Detection in Solar PV Integrated Power System," in IEEE Access, vol. 9, pp. 32672-32687, 2021, doi: 10.1109/ACCESS.2021.3060800.
2. M. Alrifaey et al., "Hybrid Deep Learning Model for Fault Detection and Classification of Grid-Connected Photovoltaic System," in IEEE Access, vol. 10, pp. 13852-13869, 2022, doi: 10.1109/ACCESS.2022.3140287.
3. A. S. Alhanaf, M. Farsadi and H. H. Balik, "Fault Detection and Classification in Ring Power System With DG Penetration Using Hybrid CNN-LSTM," in IEEE Access, vol. 12, pp.59953-59975,2024,doi:10.1109/ACCESS.2024.339416
4. D. P. Patel, I. Prashant Pathak, D. Roach and N. Yilmazer, "Robust Deep Learning Models for Fault Detection in Grid-tied Solar Inverters: A Comparative Study of LSTM, Bi-LSTM, and CNN-LSTM Architectures," 2026 IEEE Green Technologies Conference (GreenTech), Boulder, CO, USA, 2026, pp. 476-481, doi: 10.1109/GreenTech68285.2026.11471570.
5. Amiri, A. F., Kichou, S., Oudira, H., Chouder, A., & Silvestre, S. (2023). Fault Detection and Diagnosis of a Photovoltaic System Based on Deep Learning Using the Combination of a Convolutional Neural Network (CNN) and Bidirectional Gated Recurrent Unit (Bi-GRU). Sustainability, 16(3), 1012. https://doi.org/10.3390/su16031012
6. Vadlamudi, B., & T, A. (2024). Optimized Hybrid CNN-LSTM Based Islanding Detection of Solar-Wind Power System. Electric Power Components and Systems, 52(3), 337– 355. https://doi.org/10.1080/15325008.2023.2220333
7. Özcanlı, A. K., & Baysal, M. (2021). A novel Multi-LSTM based deep learning method for islanding detection in the microgrid. Electric Power Systems Research, 202, 107574. https://doi.org/10.1016/j.epsr.2021.107574
8. M. A. Khan, A. Haque and V. S. B. Kurukuru, "Machine Learning Based Islanding Detection for Grid Connected Photovoltaic System," 2019 International Conference on Power Electronics, Control and Automation (ICPECA), New Delhi, India, 2019, pp. 1-6, doi: 10.1109/ICPECA47973.2019.8975614.
9. B. Roy et al., "Deep Learning Based Relay for Online Fault Detection, Classification, and Fault Location in a Grid-Connected Microgrid," in IEEE Access, vol. 11, pp. 62674-62696, 2023, doi: 10.1109/ACCESS.2023.3285768.
10. Ramasamy, S., & Perumal, M. (2021). CNN-based deep learning technique for improved H7 TLI with grid-connected photovoltaic systems. International Journal of Energy Research, 45(14), 19851-19868. https://doi.org/10.1002/er.7030
11. M. M. Rahman, M. S. Hossain, M. S. I. Talukder and M. N. Uddin, "Transformerless Six-Switch (H6)-Based Single-Phase Inverter for Grid-Connected Photovoltaic System With Reduced Leakage Current," in IEEE Transactions on Industry Applications, vol. 58, no. 1, pp. 974-985, Jan.-Feb. 2022, doi: 10.1109/TIA.2021.3131295.
12. K. Ullah et al., "Short-Term Load Forecasting: A Comprehensive Review and Simulation Study With CNN-LSTM Hybrids Approach," in IEEE Access, vol. 12, pp. 111858-111881, 2024, doi: 10.1109/ACCESS.2024.3440631.
13. S. H. Rafi, Nahid-Al-Masood, S. R. Deeba and E. Hossain, "A Short-Term Load Forecasting Method Using Integrated CNN and LSTM Network," in IEEE Access, vol. 9, pp.

E-ISSN: 3107-5843
International Journal of Advanced Engineering and Management System
Volume 02, Issue 02, April-June 2026, pp. 67 - 77

32436-32448, 2021, doi: 10.1109/ACCESS.2021.3060654.

14. Zhang, S., Chen, R., Cao, J., & Tan, J. (2023). A CNN and LSTM-based multi-task learning architecture for short and medium-term electricity load forecasting. Electric Power Systems Research, 222, 109507. https://doi.org/10.1016/j.epsr.2023.109507

15. Karthikeyan, G., & Jagadeeshwaran, A. (2024). Enhancing Solar Energy Generation: A Comprehensive Machine Learning-Based PV Prediction and Fault Analysis System for Real-Time Tracking and Forecasting. Electric Power Components and Systems, 52(9), 1497–1512.https://doi.org/10.1080/15325008.2023.2293947