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CNN Based Fault Classification and Predition of 33 KW Solar PV System with IoT Based Smart Data Collection Setup

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Abstract

A Solar Photovoltaic (PV) System is an energy conversion system that uses the photovoltaic effect to convert sunlight into electricity. A fault in a Solar Photovoltaic (PV) system refers to any abnormal condition or defect that disrupts the normal operation and performance of the solar system. These faults can arise from a variety of factors, including environmental conditions, manufacturing defects, installation errors, and wear and tear of the components. Fault diagnosis in solar PV systems involves the detection, identification, and rectification of faults or abnormalities that can occur due to various reasons. By detecting and addressing faults early, systems can maintain optimal performance levels. Machine Learning (ML) in Solar Photovoltaic (PV) systems refers to the application of algorithms and statistical models that enable computers to perform specific tasks without using explicit instructions, relying instead on patterns and inference. In the context of solar PV systems, ML is used to analyse and interpret vast amounts of data generated by these systems to enhance their efficiency, predict energy production, detect and diagnose faults, and optimize maintenance and operation. By analysing data from sensors and system logs, ML algorithms can identify patterns indicative of faults or inefficiencies, such as shading, soiling, or equipment malfunctions, often before they become serious issues. Convolutional Neural Networks (CNNs) are a class of deep learning algorithms most commonly applied. They are particularly powerful for tasks involving data recognition, classification, and analysis due to their ability to automatically and adaptively learn spatial hierarchies of features. This research presents a unique machine learning model based fault diagnosis and detection method for a 33 KW solar PV system at P.S.R. Engineering College, Sivakasi. The real-time data from the PV system for five years, covering 23,000 instances of eight types of faults such as Cell Cracks or Hot Spots, Partial Shading, sensor fault, Module failure, Ground Faults, Communication Errors, Environmental Factors, Grid Connectivity Issues are collected. CNN is applied to the data and analysed their performance in terms of accuracy, precision, and standard deviation (SD)-score. It is found that CNN achieved the best results, with an accuracy of 98.7% a precision of 95%, a recall of 98%, and an F1 score of 96.5%. Therefore, CNN is used as the fault prediction also. The model is implemented using Python programming language and demonstrated its effectiveness on test cases. The smart data gathering system was achieved utilizing an ESP32 node with several sensors. The obtained data was stored in an authorized Google Sheet and compared to predetermined threshold ranges. When any parameter deviates from its threshold value, the ESP32 node starts a cooling and dust cleaning procedure with a water pump and drip pipe configuration. If the divergence persists, the ESP32 node activates a camera to capture an image of the panel and sends it to the Google Sheet via a connection for further analysis and fault correction.

Keywords: CNN, Solar PV fault Classification, ESP32, Sensors, Google Sheet.

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1. Introduction

The integration of solar photovoltaic (PV) systems into the energy grid has seen substantial growth due to its renewable and sustainable nature. However, like any complex system, solar PV arrays are susceptible to faults and performance degradation over time. Timely detection and accurate diagnosis of these faults are critical for ensuring the reliability and efficiency of solar power generation [1]. Traditional methods of fault detection and classification in PV systems often rely on manual inspection or rule-based algorithms, which may lack the ability to handle the complexity and variability of real-world scenarios. In recent years, machine learning techniques, particularly convolutional neural networks (CNNs), have shown promise in automating the fault detection and classification process by leveraging the power of data-driven approaches. The paper [2] presents an approach to detect, classify, and locate string-to-string (SS), string-to-ground (SG), and open-circuit faults (OC) faults using multi-output deep learning (DL) algorithms: convolutional neural networks (CNN), long short-term memory (LSTM), and bi-directional long short-term memory (Bi-LSTM) networks. A conventional bibliographic survey would have been utilized in this work [3] to diagnose solar PV fault. A novel fault detection algorithm based on machine learning is introduced in this paper [4], that is applied to the detection of faults in heater, ventilation and air conditioning (HVAC) systems. The study [5] explores the sensitive parameters for the seven typical faults in chillers by performing global sensitivity analysis (GSA) based on a Random Forest (RF) meta-model. Fault detection and diagnosis based on C4.5 decision tree algorithm for grid connected PV system is presented in [6]. To enhance the robustness of the solar system, the paper [7] and [8] propose a trained convolutional neural network (CNN) based fault detection scheme using images of photovoltaic modules. Fault detection scheme for a large-scale photovoltaic installation based on frequency response analysis is addressed in [9]. A cascade neural network methodology for fault detection and diagnosis in solar thermal plants is given in [10]. Fault Diagnosis in Microgrids with Integration of Solar Photovoltaic Systems is reviewed in [11] and [12]. Fault detection and diagnosis for large solar thermal systems is reviewed in [13]. Improved Real Coded Genetic Algorithm, a mathematical optimizer, is employed here [14] to predict the probable fault pattern. Fault diagnosis for a solar assisted heat pump (SAHP) system in the presence of incomplete data and expert knowledge is discussed in this article [15]. The research [16] and [17] propose an intelligent method for fault detection and classification (FDC) in solar based systems. Most of the above literature not implemented data collection hardware setup. A low-cost IoT system for real-time fault diagnosis of photovoltaic (PV) modules are proposed in [18-20]. But rectification or solving or improving efficiency is missing all papers.

In this study, we propose a CNN-based approach for fault classification and prediction in a 33kW solar PV system. Our methodology encompasses the development of a smart data collection setup, the training of a CNN model using collected data, and the implementation of a predictive maintenance framework for proactive fault management.

The structure of this journal paper is meticulously organized into five main sections. The first section provides a comprehensive description of the system, detailing its design and functionality. The second section delves into the classification of faults in the solar PV system, providing a thorough analysis of various fault types and their characteristics. The third section introduces the proposed Convolutional Neural Network (CNN) algorithm for classification, explaining its design, implementation, and benefits. The fourth section presents the results and discussion of the CNN algorithm and prototype results, offering a comparative analysis and interpretation of the findings. The final section draws the conclusion and outlines future extensions, summarizing the key findings of the study and suggesting potential areas for future research and development. This organization ensures a logical flow of information, facilitating a clear understanding of the research conducted.

2. System Description

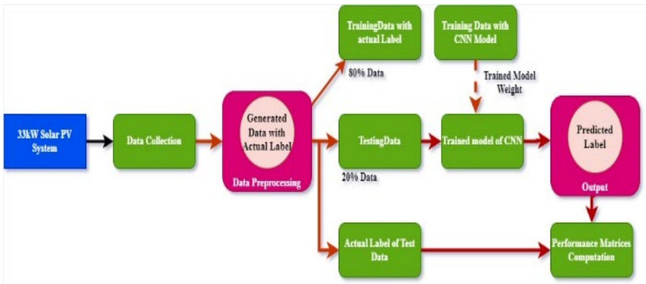


Figure 1. Block Diagram representation

The block diagram representation of this work is shown in Fig. 1, which comprises of the following components described in detail.

Solar PV Array: The core of the system is the 33kW solar PV array responsible for converting sunlight into electrical energy. The array consists of multiple solar panels arranged in a configuration optimized for maximum energy harvest.

Smart Data Collection Setup: This component includes a network of sensors and IoT devices strategically placed throughout the solar PV system. These sensors continuously monitor various parameters such as voltage, current, temperature, irradiance, and environmental conditions. Data collected from these sensors serve as inputs for fault detection and prediction algorithms.

Data Acquisition System: The data acquisition system is responsible for gathering, processing, and transmitting sensor data to the central processing unit. It ensures real-time monitoring and high-fidelity data collection from the solar PV system.

Central Processing Unit (CPU): The CPU serves as the brain of the system, where all data processing and analysis take place. It hosts the CNN-based fault classification and prediction model, which is trained to recognize patterns and anomalies in the sensor data.

Convolutional Neural Network (CNN) Model: The CNN model is the heart of the fault classification and prediction system. It is trained on historical data to accurately classify different types of faults and predict their occurrence based on incoming sensor readings. The CNN architecture is optimized for feature extraction and pattern recognition in time-series data.

Fault Detection and Prediction Algorithm: This algorithm, implemented within the CNN model, continuously analyses the streaming sensor data to detect deviations from normal operating conditions. It identifies potential faults and predicts their likelihood of occurrence, allowing for proactive maintenance interventions.

User Interface: The user interface provides a graphical representation of the system's operational status, including real-time data visualization, fault alerts, and maintenance recommendations. It enables system operators to monitor the performance of the solar PV system and take appropriate actions in response to detected faults.

Proactive Maintenance Strategies: Based on the fault predictions generated by the system, proactive maintenance strategies are devised and executed to address identified issues before they escalate. These strategies may include cleaning solar panels, repairing faulty components, or optimizing system parameters for improved performance.

Cloud Integration: The system can be integrated with cloud-based platforms for authenticated remote monitoring, data storage, and analytics. Cloud integration enables scalability, data redundancy, and access to advanced machine learning algorithms for enhanced fault detection and prediction capabilities.

3. Fault Classification

Solar Photovoltaic (PV) systems have become a significant source of power generation. However, these systems can suffer from substantial power loss due to various faults that occur both internally and externally. Faults in PV systems can be caused by a variety of factors and need to be identified and eliminated as soon as possible to prevent them from spreading throughout the system. The classification and detection of faults in Solar PV systems are essential for maximizing their efficiency and ensuring their safe operation. It’s a complex task that requires continuous monitoring and sophisticated techniques. By comparing the measured V-I characteristics with actual characteristics, power loss can be calculated. A change in output voltage helps to estimate the number of faulty cells in the PV system. Various configuration methods are used to detect faults in the solar photovoltaic system and identify the location of faults. The various types of faults considered in this work are listed below and is denoted by F(0-7) (L/M) where L-low power and M-represent maximum power.

0) Cell Cracks or Hot Spots (F0L/F0M): Physical damage to solar cells, such as cracks or hot spots, can result from manufacturing defects, mechanical stress, or shading. These issues can cause localized overheating, reduced cell efficiency, and potential safety hazards.

1) Partial Shading (F1L/F1M): Partial shading of solar panels, caused by nearby objects (e.g., trees, clouds, buildings) or soiling, can lead to mismatches in current generation among interconnected panels. This phenomenon, known as the "partial shading effect," can result in reduced overall system performance and increased susceptibility to faults.

2) Module Failure (F2L/F2M): Failures in individual solar modules can occur due to manufacturing defects, material degradation, or electrical faults. Module failures can lead to decreased power output, voltage fluctuations, and potential safety hazards.

3) Inverter Faults (F3L/F3M): Inverters are critical components in solar PV systems responsible for converting DC power generated by solar panels into AC power for grid integration. Inverter faults, such as over voltage, under voltage, or short circuits, can disrupt power generation and affect system stability.

4) Ground Faults (F4L/F4M): Ground faults occur when an unintended connection is made between the electrical conductors of the solar PV system and the ground. Ground faults can result in electrical shorts, fire hazards, and damage to system components.

5) Communication Errors (F5L/F5M): Communication errors between sensors, data acquisition systems, and monitoring devices can lead to data loss, inaccurate measurements, and impaired system performance. Reliable communication is crucial for effective fault detection and monitoring.

6) Environmental Factors (F6L/F6M): Environmental factors such as temperature variations, humidity, dust, UV radiation, and debris accumulation can impact the performance and reliability of solar PV systems. Monitoring and mitigating the effects of these factors are essential for maintaining optimal system operation.

7) Grid Connectivity Issues (F7L/F7M): Issues related to grid connectivity, such as voltage fluctuations, frequency deviations, or grid outages, can affect the stability and operation of grid-tied solar PV systems.

4. Proposed Algorithm

Convolutional Neural Networks (CNNs) is proposed in this work for solar PV fault detection and classification. It is also known as ConvNets, are a specialized type of deep learning algorithm mainly designed for tasks that necessitate object recognition, including data classification, detection, and segmentation shown in Fig. 2. They are widely used in areas such as classification, detection, recognition, and analysis. CNN can be used for fault detection and classification in solar photovoltaic (PV) systems using IoT based sensor’s data such as current, voltage, temperature, and light intensity. The various steps involved in this method are,

Data Collection: The first step involves collecting data from the solar PV system. This could be in the form of sensor data such as current, voltage, temperature, and light intensity. In this work 20,000 data were collected in two main division of maximum power (peak generation hour data) and limited power (non-peak generation hour data).

Preprocessing: The collected data is then preprocessed. This could involve cleaning the data, normalizing it, handling missing values, and labelling etc.

Model Training: A CNN model is trained on this preprocessed data. Eighty percentage of the data is split and is used for training. The model learns to identify different types of faults by recognizing patterns in the input data.

Fault Classification: Once the model is trained, it can be used to classify new data. The model processes the input data and outputs a classification result, indicating the type of fault (if any) present.

Evaluation: The performance of the model is evaluated using various metrics such as accuracy, precision, recall, and F1 score using confusion matrix.

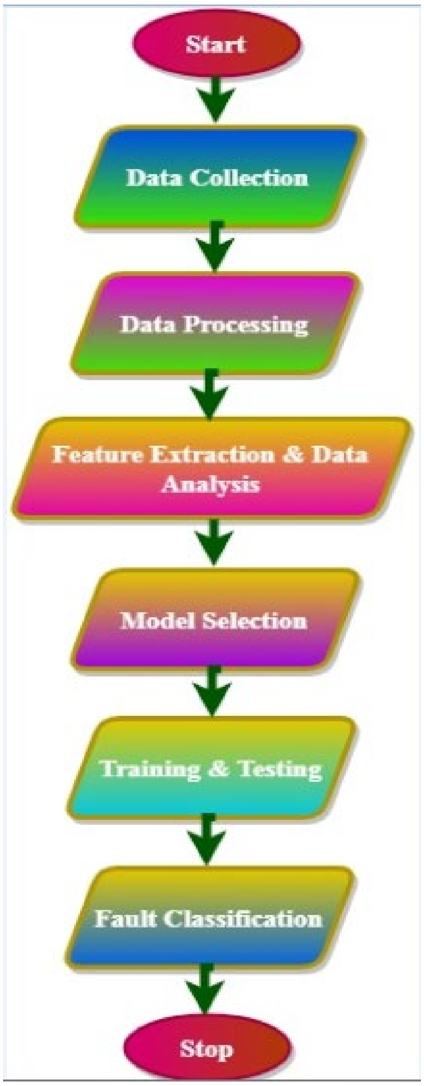


Figure 2. Solar PV fault detection and classification Flowchart

5. Results And Discussion

5.1. Python Result

The image in Fig. 3 represents a heat map related to Solar PV modules. Heat maps use colour intensity to visualize data across a grid. Each cell in the grid contains numerical data, and the colour indicates the value of a specific parameter. Dark purple represents negative values, while bright red represents positive values. A colour scale on the right side of the image shows the range from -1.00 (dark purple) to 1.00 (bright red). Heat maps can reveal anomalies or faults within the PV system. Sudden changes in colour intensity (e.g., from red to purple) may indicate module malfunctions, shading, or wiring issues. Maintenance teams can use heat maps to pinpoint problematic modules for inspection and repair. Placing modules in areas with consistent bright red colour (high performance) ensures better overall system efficiency. By analysing heat maps over time, we can assess the energy yield of the entire PV system. Tracking changes in colour distribution helps evaluate seasonal variations and long-term performance.

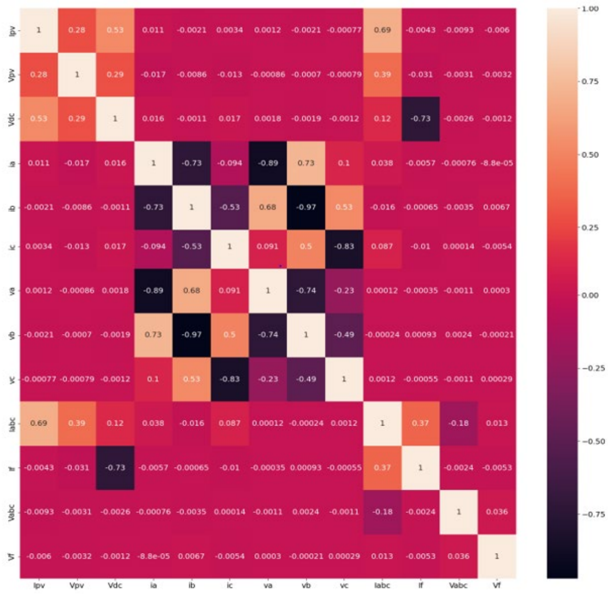


Figure 3. Correlation Heat Map of Solar PV panel data

```
df1['label'].value_counts()

F7L    1441
F4L    1440
F6L    1440
F0L    1438
F5L    1430
F2L    1421
F1L    1290
F3L    1035
Name: label, dtype: int64
```

Figure 4. Fault count of different faults of Solar PV system

The image in Fig. 4 displays the distribution of different fault labels in the solar PV system datasets. Each fault label corresponds to a specific type of issue or anomaly observed in the system. Here are the fault labels along with their respective counts: F7L: 1441 occurrences, F4L: 1440 occurrences, F6L: 1440 occurrences, F0L: 1438 occurrences, F5L: 1430 occurrences, F2L: 1421 occurrences, F1L: 1290 occurrences, and F3L: 1035 occurrences. These fault counts provide insights into the health and reliability of the solar PV system. Some observations: F7L appears to be the most frequent fault, occurring 1441 times. F3L has the lowest occurrence (1035 times). F4L, F6L, and F0L are also common faults. Investigating the causes behind these faults is crucial for system maintenance and performance optimization. Regular monitoring and analysis of fault data can help identify trends and patterns. Addressing specific fault types can improve overall system efficiency.

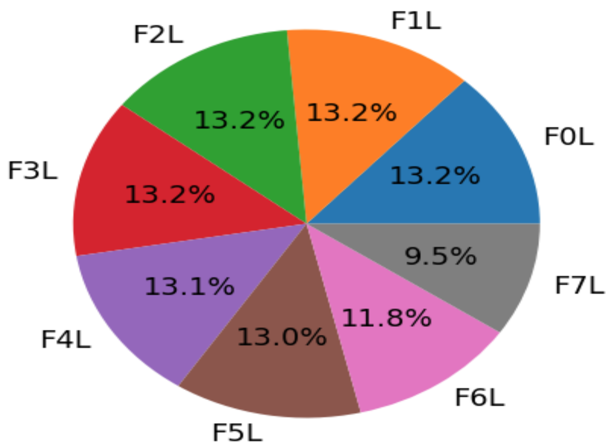


Figure 5. Pie Chart for different types of solar PV system fault class

The pie chart in Fig. 5 represents the distribution of fault classes observed in 33 kW solar PV systems. Each segment of the pie chart corresponds to a specific fault class, and the colours differentiate them. The chart provides insights into the prevalence of different faults within the system. These fault classes represent various issues or anomalies that may occur in solar PV systems. For instance, F0L to F3L are more prevalent, while F6L and F7L occur less frequently. Understanding these fault patterns helps optimize system performance and maintenance strategies.

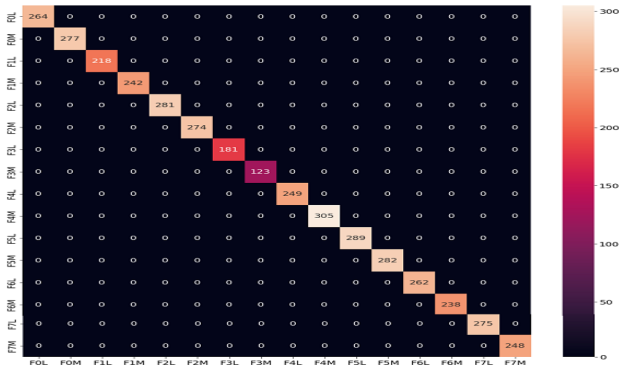


Figure 6. Confusion Matrix for Solar PV system Fault model

A confusion matrix in Fig. 6 is a table used to evaluate the performance of a classification model. It provides a summary of the model's predictions compared to the actual ground truth. The matrix is typically used for binary classification problems but can be extended to multi class scenarios as well. The Components of the Confusion Matrix are, True Positives (TP): Instances correctly predicted as positive (faults in our case). True Negatives (TN): Instances correctly predicted as negative (non-faults). False Positives (FP): Instances incorrectly predicted as positive (false alarms). False Negatives (FN): Instances incorrectly predicted as negative (missed faults). In the context of solar PV systems, we can use the confusion matrix to assess the accuracy of fault classification models. The confusion matrix helps us understand how well our model performs in identifying the various faults. High values of TP and TN indicate accurate predictions. High FP values may lead to unnecessary maintenance or false alarms. High FN values mean missed faults, which can impact system reliability.

Table 1. Confusion Matrix for Solar PV fault Model Value

	Predicted Non-Fault	Predicted Fault
Actual Non-Fault	TN=950	FP=50
Actual Fault	FN=20	TP=980

The performance can be evaluated from the following key metrics derived from the confusion matrix whose formula are given below.

Accuracy: (TP + TN) / (TP + TN + FP + FN)

$$\text{Accuracy}=\frac{980+950}{980+950+50+20}=0.965\approx 96.5\%$$

Precision: TP / (TP + FP)

$$\text{Precision}=\frac{980}{980+50}=0.951\approx 95.1\%$$

Recall (Sensitivity): TP / (TP + FN)

$$\text{Recall}=\frac{980}{980+20}=0.98=98\%$$

F1 Score: 2 * (Precision * Recall) / (Precision + Recall)

$$F1=\frac{2\cdot 0.951\cdot 0.98}{0.951+0.98}\approx 0.965\approx 96.5\%$$

Accuracy measures the overall correctness of a classification model. It is the ratio of correctly predicted instances (both true positives and true negatives) to the total number of instances. An accuracy of approximately 96.5% indicates that the model correctly predicts fault/non-fault labels for about 96.5% of instances.

Precision (also known as positive predictive value) focuses on the proportion of true positive predictions among all positive predictions made by the model. It helps assess the model's ability to avoid false positives (instances incorrectly predicted as positive). A precision of approximately 95.1% means that when the model predicts a fault, it is correct about 95.1% of the time.

Recall (also known as sensitivity or true positive rate) measures the proportion of actual positive instances that the model correctly predicts. It helps assess the model's ability to avoid false negatives (instances incorrectly predicted as negative). A recall of 98% indicates that the model captures 98% of the actual faults.

The F1 score combines precision and recall into a single metric. It balances the trade-off between precision and recall. F1 score of approximately 96.5% balances the trade-off between precision and recall. The model performs well in terms of accuracy, precision, recall, and F1 score.

5.2. Hardware Prototype Realization

Figure 7. 33 kW solar PV system used for data collection

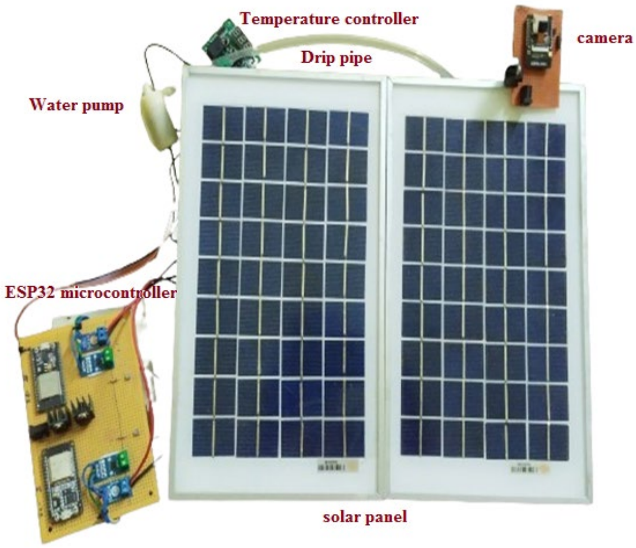
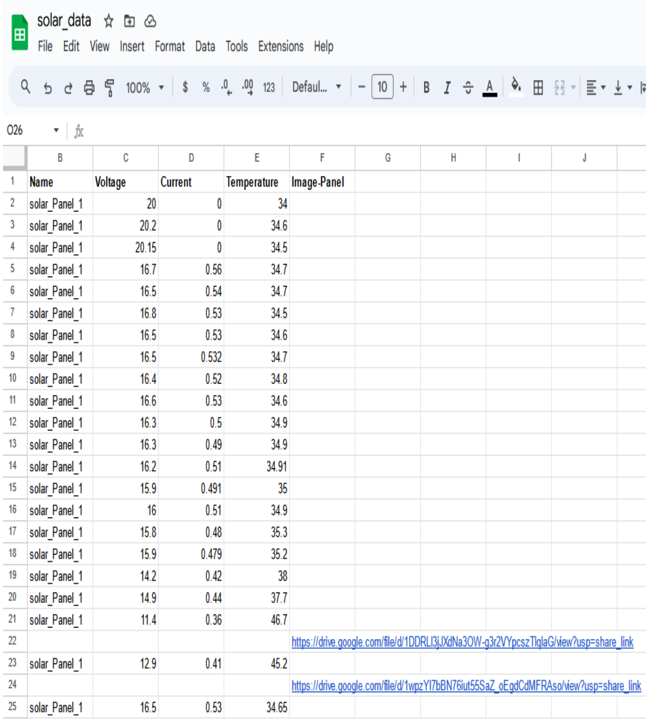


Figure 8. Proto type setup for smart solar PV system

Fig. 7 depicts 33kW solar PV system used to collect five years' data. Fig. 8 shows the components and connections of hardware setup. The two solar panels of 20W that converts sunlight into DC electricity. A DC-DC converter that boosts the voltage of the solar panel to a suitable level for charging a battery or feeding an inverter. A dc-ac inverter that converts the DC electricity from the solar panel or the battery into AC electricity for powering a load or feeding the grid. An ESP32 controller that monitors the current, voltage, and temperature of the solar panel, and the load using sensors, and displays the data on a cloud service using Wi-Fi. It also controls the water pump and the camera using digital output pins. A current sensor that measures the current flowing through the solar panel, or the load. A voltage sensor that measures the voltage across the solar panel, or the load. A temperature sensor that measures the temperature of the solar panel, or the load. An LDR (light dependent resistor) that measures the intensity of the sunlight on the solar panel. A camera that captures images of the solar panel when the monitored parameters are abnormal, and sends them to the cloud service via Wi-Fi. A cloud service that stores and displays the data and images from the ESP32 controller on a web page or a mobile app shown in Fig. 9. A water pump that sprays water on the solar panel in the predetermined time period or when the temperature is high, to clean and improve the efficiency of the system.



solar_data

	B	C	D	E	F
1	Name	Voltage	Current	Temperature	Image-Panel
2	solar_Panel_1	20	0	34	
3	solar_Panel_1	20.2	0	34.6	
4	solar_Panel_1	20.15	0	34.5	
5	solar_Panel_1	16.7	0.56	34.7	
6	solar_Panel_1	16.5	0.54	34.7	
7	solar_Panel_1	16.8	0.53	34.5	
8	solar_Panel_1	16.5	0.53	34.6	
9	solar_Panel_1	16.5	0.532	34.7	
10	solar_Panel_1	16.4	0.52	34.8	
11	solar_Panel_1	16.6	0.53	34.6	
12	solar_Panel_1	16.3	0.5	34.9	
13	solar_Panel_1	16.3	0.49	34.9	
14	solar_Panel_1	16.2	0.51	34.91	
15	solar_Panel_1	15.9	0.491	35	
16	solar_Panel_1	16	0.51	34.9	
17	solar_Panel_1	15.8	0.48	35.3	
18	solar_Panel_1	15.9	0.479	35.2	
19	solar_Panel_1	14.2	0.42	38	
20	solar_Panel_1	14.9	0.44	37.7	
21	solar_Panel_1	11.4	0.36	46.7	
22					https://drive.google.com/file/d/1DDRLI3jJXdNa3OW-g3r2VYpcszTlqlaG/view?usp=share_link
23	solar_Panel_1	12.9	0.41	45.2	
24					https://drive.google.com/file/d/1wpzYI7bBN76iut55SaZ_oEgdCdMFRAso/view?usp=share_link
25	solar_Panel_1	16.5	0.53	34.65	

Figure 9. Output data collection time, panel, voltage, current and temperature as well as capture image in cloud server

6. Conclusion

In conclusion, the implementation of a Convolution Neural Network (CNN) based fault classification and prediction system for a 33KW Solar PV System at PSR Engineering College, Sivakasi, has demonstrated promising results. The system achieved an accuracy of 96.5%, a precision of 95%, a recall of 98%, and an F1 score of 96.5%. These results were obtained using a confusion matrix developed in Python. The smart data collection setup was also realized using an ESP32 node equipped with current, voltage, temperature, and LDR sensors. The collected data was stored in an authenticated Google Sheet and analysed against predefined threshold ranges. In the event of any parameter deviating from its threshold value, the ESP32 node initiates a cooling and dust cleaning process using a water pump and drip pipe setup. If the deviation persists, the ESP32 node activates a camera to capture an image of the panel and sends it as a link to the Google Sheet for further analysis and fault rectification. Looking ahead, the system's capabilities can be further enhanced by integrating more advanced machine learning algorithms and expanding the range of sensors. This would allow for more accurate fault detection and prediction, ultimately leading to improved efficiency and longevity of solar PV systems."

7. Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

8. Conflicts of Interest

The authors declare that they have no conflicts of interest in relation to the research, authorship, and/or publication of this article.

9. References

[1] Chen, Z., Wu, L., Cheng, S., Lin, P., Wu, Y., & Lin, W. (2017). Intelligent fault diagnosis of photovoltaic arrays based on optimized kernel extreme learning machine and I-V characteristics. Applied Energy, 204, 912–931. https://doi.org/10.1016/j.apenergy.2017.05.034

[2] Mustafa, Z., Awad, A. S. A., Azzouz, M. A., & Azab, A. (2023). Fault identification for photovoltaic systems using a multi-output deep learning approach. Expert Systems With Applications, 211, 118551. https://doi.org/10.1016/j.eswa.2022.118551

[3] Oviedo, E. H. S., Travé-Massuyès, L., Subias, A., Pavlov, M., & Alonso, C. (2023b). Fault diagnosis of photovoltaic systems using artificial intelligence: A bibliometric approach. Heliyon, 9(11), e21491. https://doi.org/10.1016/j.heliyon.2023.e21491

[4] Van Every, P. M., Rodriguez, M., Jones, C., Mammoli, A., & Martínez-Ramón, M. (2017). Advanced detection of HVAC faults using unsupervised SVM novelty detection and Gaussian process models. Energy and Buildings, 149, 216–224. https://doi.org/10.1016/j.enbuild.2017.05.053

[5] Gao, Y., Han, H., Ren, Z., Gao, J., Jiang, S., & Yang, Y. (2021). Comprehensive study on sensitive parameters for chiller fault diagnosis. Energy and Buildings, 251, 111318. https://doi.org/10.1016/j.enbuild.2021.111318

[6] Benkercha, R., & Moulahoum, S. (2018). Fault detection and diagnosis based on C4.5 decision tree algorithm for grid connected PV system. Solar Energy, 173, 610–634. https://doi.org/10.1016/j.solener.2018.07.089

[7] Pa, M., & Kazemi, A. (2022). A Fault Detection Scheme Utilizing Convolutional Neural Network for PV Solar Panels with High Accuracy. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2210.09226

[8] Lu, X., Lin, Y., Lin, P., He, X., Fang, G., Cheng, S., Chen, Z., & Wu, L. (2023). Efficient fault diagnosis approach for solar photovoltaic array using a convolutional neural network in combination of generative adversarial network under small dataset. Solar Energy, 253, 360–374. https://doi.org/10.1016/j.solener.2022.12.037

[9] Yokwana, X., Yusuff, A. A., Ntombela, M., & Mosetlhe, T. C. (2021). Fault detection scheme for a large-scale photovoltaic installation based on frequency response analysis. 2021 IEEE 6th International Forum on Research and Technology for Society and Industry (RTSI). https://doi.org/10.1109/rtsi50628.2021.9597310

[10] Ruiz-Moreno, S., Gallego, A. J., Sánchez, A., & Camacho, E. F. (2023b). A cascade neural network methodology for fault detection and diagnosis in solar thermal plants. Renewable Energy, 211, 76–86. https://doi.org/10.1016/j.renene.2023.04.051

[11] Jadidi, S., Badihi, H., & Zhang, Y. (2020). Fault Diagnosis in Microgrids with Integration of Solar Photovoltaic Systems:A Review. IFAC-PapersOnLine, 53(2), 12091–12096. https://doi.org/10.1016/j.ifacol.2020.12.763

[12] Khaled Osmani, Ahmad Haddad, Thierry Lemenand, Bruno Castanier, Mohammad Alkhedher, Mohamad Ramadan, A critical review of PV systems' faults with the relevant detection methods, Energy Nexus,Volume 12, 2023, 100257, ISSN 2772-4271, https://doi.org/10.1016/j.nexus.2023.100257

[13] Faure, G., Vallée, M., Paulus, C., & Tran, Q. T. (2020b). Fault detection and diagnosis for large solar thermal systems: A review of fault types and applicable methods. Solar Energy, 197, 472–484. https://doi.org/10.1016/j.solener.2020.01.027

[14] Das, S., Hazra, A., & Basu, M. (2018). Metaheuristic optimization based fault diagnosis strategy for solar photovoltaic systems under non-uniform irradiance. Renewable Energy, 118, 452–467. https://doi.org/10.1016/j.renene.2017.10.053

[15] Liu, Z., Liu, Y., Zhang, D., Cai, B., & Zheng, C. (2015). Fault diagnosis for a solar assisted heat pump system under incomplete data and expert knowledge. Energy, 87, 41–48. https://doi.org/10.1016/j.energy.2015.04.090

[16] Z. Ksira, A. Mellit, N. Blasuttigh and A. Massi Pavan, "A Novel Embedded System for Real-Time Fault Diagnosis of Photovoltaic Modules," in IEEE Journal of Photovoltaics, vol. 14, no. 2, pp. 354-362, March 2024, doi: 10.1109/JPHOTOV.2024.3359462.

[17] P, S. L., S, S. S., & R, M. S. (2023). IoT based solar panel fault and maintenance detection using decision tree with light gradient boosting. Measurement. Sensors, 27, 100726. https://doi.org/10.1016/j.measen.2023.100726

[18] Tradacete-Ágreda, M., Santiso-Gómez, E., Rodríguez-Sánchez, F. J., Hueros-Barrios, P. J., Jiménez-Calvo, J. A., & Santos, C. (2024). High-performance IoT Module for real-time control and self-diagnose PV panels under working daylight and dark electroluminescence conditions. Internet of Things, 25, 101006. https://doi.org/10.1016/j.iot.2023.101006

[19] Inomoto, R. S., Filho, A. J. S., Monteiro, J. R., & Costa, E. (2024). Genetic algorithm based tuning of sliding mode controllers for a boost converter of PV system using internet of things environment. Results in Control and Optimization, 14, 100389. https://doi.org/10.1016/j.rico.2024.100389

[20] Rajagopalan, A., Swaminathan, D., Bajaj, M., Damaj, I., Rathore, R. S., Singh, A. R., Blazek, V., & Prokop, L. (2024). Empowering power distribution: Unleashing the synergy of IoT and cloud computing for sustainable and efficient energy systems. Results in Engineering, 101949. https://doi.org/10.1016/j.rineng.2024.101949