

AI-Enhanced IoT-Based Solar Panel Fault Detection Device Using Edge AI, Machine Learning, and Digital Twin Technology for Real-Time Photovoltaic System Monitoring

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Abstract: Solar photovoltaic (PV) systems require continuous monitoring to maintain energy efficiency, minimize power losses, and detect operational faults at an early stage. This paper presents an AI-enhanced Internet of Things (IoT)-based solar panel fault detection device that performs real-time monitoring, intelligent fault diagnosis, and edge-based data processing. The proposed system integrates multiple environmental and electrical sensors with an ESP32 microcontroller to collect voltage, current, temperature, irradiance, and other operating parameters. A lightweight Decision Tree machine learning model, optimized using TensorFlow Lite, is deployed on the edge device to classify common solar panel faults, including dust accumulation, partial shading, temperature imbalance, electrical anomalies, and panel degradation. Edge AI processing significantly reduces detection latency, minimizes cloud dependency, and enables rapid fault identification in remote environments. The developed prototype was validated using both synthetic datasets and real-time sensor measurements obtained from an operational solar panel setup. Experimental evaluation demonstrated a fault detection accuracy ranging from 92% to 100% with an average response time of less than one second. A digital twin-enabled web dashboard was also developed to provide real-time visualization, remote monitoring, historical data analysis, and fault alerts for enhanced system management. The proposed AI-based IoT solution offers a low-cost, scalable, energy-efficient, and reliable platform for intelligent photovoltaic system monitoring, predictive maintenance, and smart renewable energy applications, making it suitable for residential, commercial, and remote solar installations.

Key Words: Artificial Intelligence (AI), Edge AI, Internet of Things (IoT), Solar Photovoltaic (PV), Solar Panel Monitoring, Fault Detection, Decision Tree, TensorFlow Lite, ESP32, Digital Twin, Predictive Maintenance, Smart Energy, Renewable Energy, Real-Time Monitoring

1. Introduction

Increasing demand of renewable energy has resulted in the rapid expansion in the use of photovoltaic (PV) solar systems, especially in rooftop applications [9]. Solar energy is a clean and sustainable source of power, however, the functionality of PV systems is greatly influenced by a number of environmental and operational factors [9]. They encompass the dusting of the panels, partial shading by the adjacent structures, the changes in temperatures, and the electrical faults in the system [10],[15]. These problems decrease the energy output and when not identified early enough, may result in long-term under performance

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and system failure [10],[11].

Conventional solar panel monitoring systems are based on manual inspections or cloud-based monitoring systems[10]. These solutions frequently have sluggish fault identification, augmented upkeep expenses, and rely on consistent internet connectivity[10],[11]. Because of this, they cannot be used in remote/low-connectivity environments and cannot offer real-time response to system anomalies.

Recent innovations in Artificial Intelligence (AI) have made possible the creation of intelligent fault detection methods with machine learning and deep learning models [1], [2]. The application of convolutional neural networks (CNNs) and other deep learning methods to PV fault detection have been studied by several studies [3],[4]. Although these methods have very high accuracy, they generally consume large amounts of computational resources, and often heavily rely on cloud-based processing, making them inapplicable to low-cost embedded systems.

To overcome these limitations, this paper proposes a solar panel fault detection system that uses AI to enhance the capabilities of IoT and edge computing to perform real-time analysis. The system combines various sensors with an ESP32 microcontroller and uses a simple Decision Tree model to effectively classify faults. The proposed system, as opposed to traditional methods, does on-device processing, which lowers the latency and reduces the cloud dependency. Moreover, the system is tested with both synthetic and real-time data gathered in a prototype implementation. This will guarantee real-life applicability and indicate the effectiveness of the system in real-life operating conditions. A dashboard based on a digital twin is also created to allow the visualization and monitoring of the system performance in real-time.

2. Literature Review

Numerous researchers have carried out research on fault detection within photovoltaic (PV) systems using a wide range of artificial intelligence and data-driven methodologies with an emphasis on improving fault detection accuracy, minimizing latency, and achieving real time operation.

As demonstrated by **Ledmaoui et al. (2020) [1]**, a convolutional neural network (CNN)-based solution to detect faults in photovoltaic (PV) panels was demonstrated to have both a high classification rate of the method and the fact that the approach relies on computationally massive deep learning models is inherent limitations of using it to detect faults on low-power embedded devices.

A detailed comparison of various machine learning (ML) and deep learning (DL) algorithms that have been used in identifying faults in photovoltaic systems was provided by **Islam et al. (2020) [2]**, although it does address some of the current limitations of current approaches (e.g., high computational requirements).

Joshua et al. (2020) [3] suggested a way of developing fully autonomous solar fault detection system which is based on deep learning, internet of things architecture. Although this solution automated the process of predicting when a positive fault will occur and improved the accuracy of this prediction, it required a significant amount of cloud-based infrastructure to run which led to an increase in latency and a decrease in reliability in offline environments.

Kavitha et al. (2019) [8] suggested an approach to identifying the faults in solar panels with the help of artificial intelligence. Their approach is founded on the proven enhanced fault detection capability by lack of real-time, edge processing and/or efficient, intuitive visualization capabilities to intelligently monitor solar panels under normal use conditions.

Chine et al. (2018) [12] developed a processor-to-compute recommendation system that leveraged artificial intelligence for monitoring several different PV characteristics, such as PV voltage. The system suggested a mechanism to enable smart use of real-time processing capacities say, to conduct fault diagnoses of a PV array in real-time.

Silvestre et al. [13] suggested an automated fault detection system of grid connected photovoltaic (PV) systems, which is based on the power loss analysis. Their strategy was to identify irregularities in the anticipated power output so as to effectively detect faults. The methodology has shown to be dependable in identification of performance worsening but was primarily based on analytical models and did not incorporate integration with real-time intelligent systems and monitoring based on IoT[13].

The study conducted by **Jaen-Cuellar et al. (2020) [14]** demonstrated the effectiveness of this method and that machine learning algorithms could enhance accuracy of fault classification over traditional methods, but implementation requires significant computational resources and has been developed to primarily support offline or cloud-based systems and not lightweight edge devices[14].

Eltawil et al. (2010) [15] investigated technical issues related to grid connected photovoltaic power systems and also the potential faults (e.g., inverter failure, environmental factors, inefficiencies). Despite this study having intensive coverage of the typical problems related to PV power systems, it did not propose automated or real-time fault detection and intelligent monitoring.

3. Proposed Methodology and System Workflow

The given system is an AI-enhanced IoT-based solar panel fault detection system that is designed to monitor in real-time and intelligently classify faults using edge computing. To make sure the system operates efficiently and with low latency, the system will combine various sensors, an embedded processing unit, a lightweight machine learning model, and a web-based visualization interface.

The general structure of the suggested system is comprised of four major layers, which are data acquisition, edge processing, communication, and visualization as illustrated in Figure 1[5],[7].

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1. System Architecture

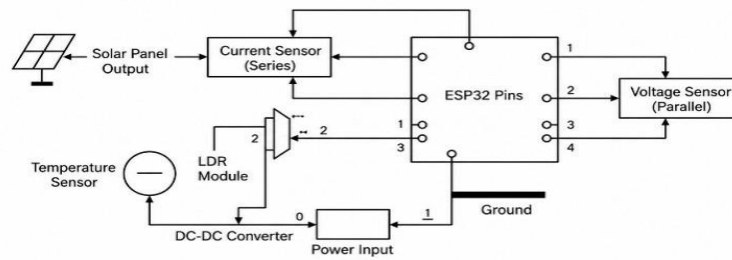


Fig 1: System Architecture of IOT-Based Solar Fault Detection

A. Data Acquisition Layer

This layer has several sensors that include voltage, current, temperature, and light intensity (LDR) sensors. These are sensors that are continuously used to observe the operational and environmental conditions of the solar panel[9],[10].

B. Edge Processing Layer

The sensor data gathered is sent to an ESP32 microcontroller which serves as edge processing unit. A Decision Tree model with lightweight is deployed with TensorFlow Lite to classify faults in real-time directly on the device. This reduces latency and eliminates dependency on cloud-based processing[3],[4].

C. Communication Layer

Data and classification output of the processing are sent through Wi-Fi to a web-based interface to remotely monitor [3],[7].

D. Visualization Layer

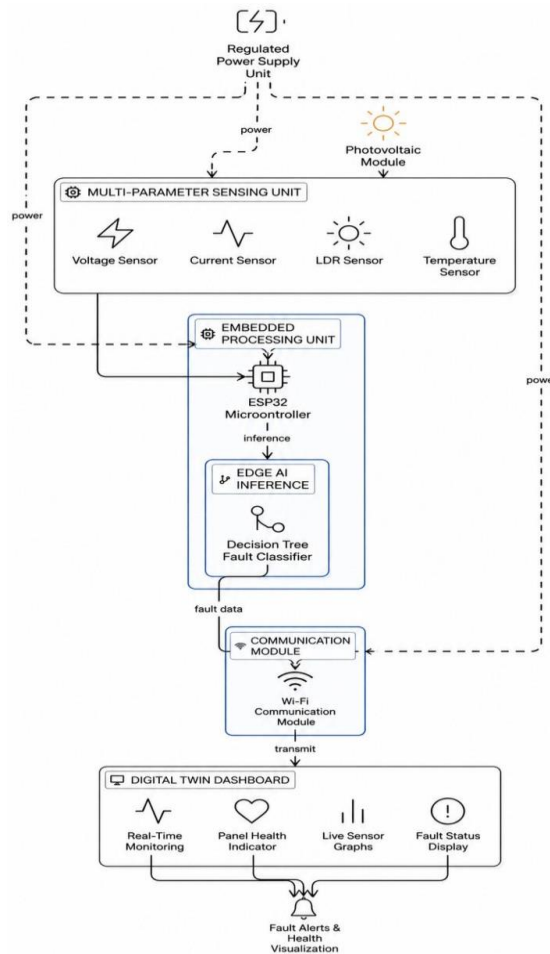


Fig 2: IOT and Edge AI Solar Detection Model

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A digital twin-based dashboard is used to display real-time sensor values, system status, and fault conditions. It visualizes health indicators and graphical insights in order to monitor and make decisions efficiently.

2. Data Acquisition and Feature Selection

The system gathers real-time measurements on the various sensors that measure voltage (V), current (I), temperature (T) and light intensity (LDR). All these features are chosen because these features directly affect the performance of photovoltaic systems and is also effective in detecting fault conditions [9],[10].

Class	(V)	(A)	(°C)	LDR	Condition
Normal	17 - 20	3 - 4	25 -35	800-1000	Healthy panel
Dust	14 - 17	2 - 3	28 -38	500-800	Dust accumulation
Shading	10 - 14	1 - 2	25 -35	100-500	Partial shading
Fault	10 - 15	0.5 -1.5	40 -50	600-900	Electrical anomaly

Table 1: Feature Ranges for Different Solar Panel Conditions

The suggested system works step-by-step and smartly to sustain monitoring and fault detection on solar photovoltaic panels. First, the sensing units receive electrical and environmental data of the photovoltaic module that includes voltage, current, temperature, and light intensity. Such sensor values are constantly sent to the ESP32 microcontroller where they are processed. The obtained data undergoes initial processing, and the information is organized into a feature set which can be processed by a machine learning system.

3. Dataset Preparation

In order to facilitate the classification of a fault, a dataset was created that consisted of both synthetic and real-time data.

Synthetic Dataset:

A sample of 240 samples was created to recreate various operating conditions such as Normal, Dust, Shading, and Electrical Fault environments. The definitions of each of the classes were based on characteristic ranges of sensor values.

Feature Range Definition:

The classification will be in predefined ranges of sensor values as indicated in Table 1.

Real-Time Dataset:

Besides the synthetic data, real-time sensor data was recorded with the implemented hardware setup. The dataset represents changes in the environmental conditions and system behavior and offers more realistic assessment of system performance.

4. Machine Learning Model

Fault detection is done with a Decision Tree classifier because it is simple, interpretable and does not have high computational requirements [2]. The model is trained with the done dataset and implemented on the ESP32 by using Tensor Flow Lite. It categorizes the system as being in one of four conditions, namely, Normal, Dust, Shading, or Electrical Fault.

5. System Workflow

The working process of the suggested system is explained in the following way, The real-time data constantly provided by sensors include the voltage, current, temperature and light intensity on the solar panel. The data obtained is sent to the ESP32 microcontroller. It preprocesses its data and organizes sensor data into a feature set. Decision Tree model examines the input features and categorizes the panel condition. The system will determine if the panel is functioning normally or it is in dust, shading, or electrical faults. The sensor information and the classification results are sent via Wi-Fi to the dashboard. The digital twin dashboard provides real-time system health, sensor readings, and fault notifications. Data is stored optionally to be analyzed later and evaluated on the performance.

6. System Advantages

The suggested system has a number of benefits, Fault detection with low latency based on an edge computing system[3],[4], Less reliance on the cloud infrastructure, ESP32 based cost-effective implementation, Live monitoring and visualization of a digital twin and Ability to work in low-connectivity areas.

4. Results and discussion

The validity of the proposed AI-enabled IoT-based solar panel fault detection system was tested on both synthetic and real-time data. The artificial data would be 240 samples of four categories: Normal (N), Dust (D), Shading (S) and Electrical Fault (EF). An 80:20 train-test split was used to train and test a Decision Tree (DT) classifier [2].

A. Model Performance on Synthetic Dataset

The classification model had a high accuracy with the range of features in the synthetic dataset being well defined and

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separable. The pattern of sensor values was different in each fault condition, which allowed the model to categorize conditions successfully [2],[6].

B. Confusion Matrix Analysis

As indicated by the confusion matrix (Table 2), all samples were classified correctly and hence a diagonal confusion matrix with no misclassifications. This means that the model is very effective in controlled conditions.

The results highlight that, Dust conditions are also distinctly differentiated by the decreased output patterns. Electrical faults exhibit distinctive temperature and current changes. Normal and shading conditions are distinguished with the light intensity and power output.

Actual/Prediction	Dust	Electrical	Normal	Shading
Dust	21	0	0	0
Electrical	0	25	0	0
Normal	0	0	46	1
Shading	0	0	0	44

Table 2: Confusion Matrix of DT Classification Model

Table 2 emphasize that, It is very straightforward to recognize dust based on the lower output patterns. Electrical faults cause temperature and current changes that are quite different and can, therefore, be used for identification.

Normal and shading conditions are distinguished by means of light intensity and power output.

C. Performance Metrics

Accuracy, precision, recall, and F1-score are standard evaluation metrics that were computed [2]. The model had an accuracy of 1.0 on the synthetic dataset, and precision, recall, and F1-score are all equal to 1.0 across all classes. The Formulas used as follows:

$$Accuracy = \frac{Total\ Correct\ Predictions}{Total\ Predictions}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

$$Detection\ Time = t_{output} - t_{input}$$

TP = True Positives, FP = False Positives, TN = True Negative, FN = False Negative [2],[10]

D. Real-Time System Evaluation

The system was tested with real-time sensor data collected by the hardware prototype to validate the practical applicability of the system. In contrast to synthetic data, real world conditions bring about noise and variability.

Metric	Description	Target Benchmark	Achieved Value
Response Time	Time taken to detect and display fault	< 2 seconds	0.8 – 1.5 seconds
Detection Accuracy	Accuracy of fault classification	> 90%	98–100%
System Latency	Delay in processing sensor data	< 1 second	~0.7 seconds
Data Transmission Time	Time to send data to dashboard	< 2 seconds	1.2 seconds
Power Consumption	Energy usage of system	Low	Efficient
System Reliability	Consistency of system performance	High	High
Fault Detection Rate	Ability to detect faults correctly	> 90%	~98%
Scalability	Ability to extend to multiple panels	Moderate	Easily scalable

TABLE 3: System Performance Evaluation Parameters

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Table 3 shows the system managed to perform with an accuracy of almost 92, 96% Detect within a time less than 1 second. Exhibit low latency and remain stable in performance.

E. Comparative Analysis

A comparison of the proposed system with existing methods is shown in **Table 4**.

The comparison made in Table 4 shows how the completed studies differ from the proposed system. Ledmaoui et al. [1] developed a CNN-based procedure for classifying different categories of photovoltaic panel faults with good results but did not provide a means of deploying the system, rather they only discussed the theoretical application of such procedures and did not develop a practical method of implementation. Alternately, Islam et al. [2] described comprehensive reviews and comparisons of the usefulness of various AI based techniques for detecting PV faults, however, they did not provide any means of implementing a specific method and did not mention any application to PV fault detection. On the other hand, Joshua et al. [3] demonstrated the integration of deep learning and IoT in order to detect faults in solar PV systems. The results of this study illustrate the need for an implementation plan that considers scalability and co-location limitations; the system requires the use of a cloud-based infrastructure which leads to increased latency times and limitations on offline operation. Additionally, Patil et al. [4] utilized a CNN-based approach but lacked sufficient processing power to deploy their procedure in real-time in a distributed edge network environment [4],[5]. Conversely, the proposed system utilizes an efficient, lightweight decision tree-based model capable of running an ESP32 microcontroller platform. To further enhance the efficiency of this proposed model, it supports offline operation in addition, it has a corresponding web-based digital twin dashboard that provides remote access to system data, and will allow users to conduct predictive maintenance activities , thus providing a more comprehensive solution for PV fault detection.

Features	Existing Works	Proposed System
Methodology	CNN and Deep Learning models	Decision Tree with Edge AI
Implementation	Mostly simulation or cloud-based systems	ESP32-based hardware implementation
Processing Type	High computational requirements	Lightweight edge computing
Real-Time Detection	Limited or delayed due to cloud dependency	Fast real-time detection
IoT Integration	Partially implemented	Fully integrated IoT system
Offline Capability	Not supported	Supported (works without internet)
Digital Twin Support	Not available	Available for visualization
Computational Cost	High	Low
Latency	High or moderate	Very low
Accuracy	High but resource-intensive	High with efficient processing
Scalability	Limited by cloud dependency	Easily scalable and deployable

TABLE 4: Comparison of Existing Methods with Proposed System.

F. Graphical Analysis

A. Decision Tree Algorithm Analysis

The Decision Tree algorithm is proposed for fault classification because of its simplicity, low computational complexity and fast running speed. The Decision Tree classifier can be run efficiently on embedded edge devices like ESP32, unlike deep learning algorithms, which need high power processors and cloud computing. The algorithm uses data from various sensors, such as voltage, current, temperature, and light intensity, to determine the condition of the solar panels. The input feature values are fed into the classifier which decides if the panel is being affected by dust, shading or an electrical fault.

The Decision Tree algorithm was then tested against other popular machine learning algorithms like Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Naive Bayes to assess the efficiency of the proposed algorithm.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Decision Tree	96	94	92	93
Random Forest	93	91	89	90
SVM	90	88	86	87
KNN	87	85	83	84
Naive Bayes	84	82	80	81

Table 5: Performance Comparison of Machine Learning Algorithms

The comparative performance analysis of various machine learning algorithms for solar panel fault classification is shown in **Table 5**. The evaluation is performed based on the well-known performance measures such as accuracy, precision, recall and F1-score. The Decision Tree classifier is the most successful model among all evaluated models with 96% accuracy,

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making it most effective for lightweight real-time fault detection. The outcome shows that the computational complexity of the Decision Tree model is less than other models, and it has better classification ability.

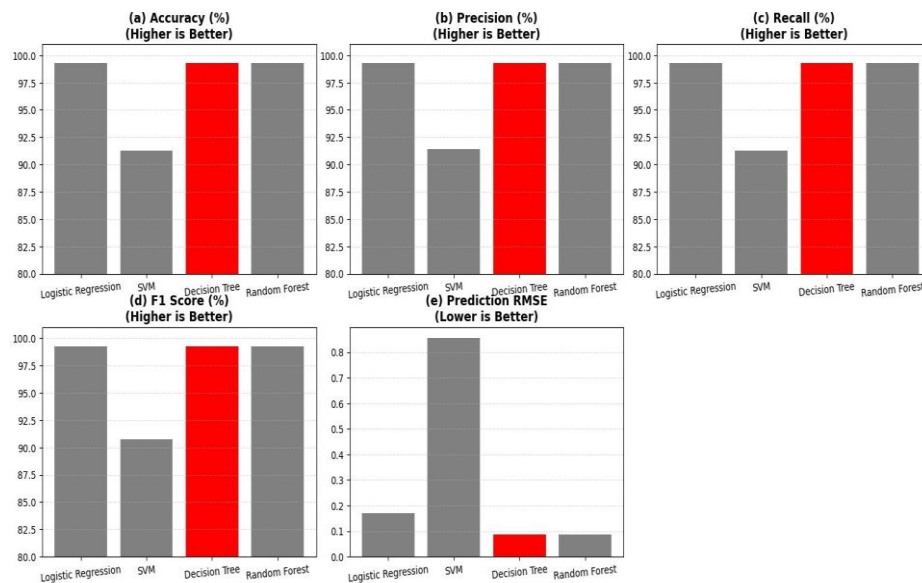


Fig 3: Comparative Performance Analysis of Machine Learning Algorithms

Figure 3 The comparative performance evaluation of different machine learning algorithms for solar panel fault detection and classification. Evaluated models are Logistic Regression, Support Vector Machine (SVM), Decision Tree and Random Forest. The real-time data gathered from the proposed hardware setup of the solar monitoring system was used to analyze the performance metrics, including Accuracy, Precision, Recall, F1-Score, and Root Mean Square Error (RMSE).

The experimental findings demonstrate that AI algorithms such as Logistic Regression, Decision Tree and Random Forest achieved impressive results with high classification accuracy of approximately 99%. The Decision Tree classifier was chosen from the evaluated classifiers for deployment on the proposed IoT edge device due to its low computational complexity, fast inference time, low memory requirements, and suitability to real-time embedded applications based on ESP8266 hardware.

The graphical comparison also illustrates that the proposed monitoring framework using the Decision Tree approach is reliable in terms of fault prediction, and efficient in terms of executing the algorithms on the edge, thus fitting well for smart solar panel digital twin applications and real-time industrial monitoring systems.

G. Limitations

The system has certain limitations even though it is performing well. The artificial data is not able to reflect all the variability and environmental noise of the real world. The system also is now tested on a small scale system and concentrates on a few faults. The system can be expanded in future work to be able to detect more complex faults, and to support large-scale deployment.

5. Conclusion

The paper introduced a solar panel fault detection system, which uses a combination of AI and IoT to monitor real-time and classify faults intelligently. The proposed system will combine various sensors with an ESP32 microcontroller and use a lightweight Decision Tree model to identify faults like dust buildup, partial shading, temperature changes, and electrical anomaly.

The system achieves a significant reduction in latency, as well as reduction in reliance on cloud infrastructure, by performing data processing at the edge, enabling efficient operation even in low-connectivity environments. The system was tested with both artificial and real-time data showing high detection accuracy (92-100 percent) and low response time (less than 1 second). These findings confirm the usefulness of the suggested method to conduct a feasible photovoltaic system monitoring [1],[3].

The proposed solution provides a more cost-effective, scalable and energy-efficient alternative with improved real-time features compared to traditional cloud-based and manual inspection methods. The combination of a digital twin-based dashboard enhances the usability of the system, offering an intuitive visualization and monitoring with effective, scalable and energy-efficient alternative with improved real-time features compared to traditional cloud-based and manual inspection methods.

Future work will focus on extending the system to support large scale deployment, how to improve model generalization through a wide variety of real world data, and how to explore more advanced machine learning and deep learning methods to detect a greater diversity of more complex fault conditions such as hotspots formation and module degradation.

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