IoT-based monitoring and shading faults detection for a PV water pumping system using deep learning approach

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ABSTRACT

One of the major challenges facing photovoltaic (PV) systems is fault detection. Artificial intelligence (AI) is one of the main popular techniques used in error detection due to its ability to extract signal and image features. In this paper, a deep learning approach based on convolutional neural network (CNN) and internet of things (IoT) technology are used to detect and locate shading faults for a PV water pumping system. The current and voltage signals generated by the PV panels as well as temperature and radiation were used to convert them into 3D images and then upload to a deep learning algorithm. The PV system and fault detection algorithms were simulated by MATLAB. The obtained results indicate that the performance of the proposed deep learning approach to detect and locate faults is better than the traditional statistical methods and other machine learning methods.

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1. INTRODUCTION

The past two decades have witnessed an increasing global growth in the use of renewable energy sources to generate clean energy instead of using traditional energy sources [1]. This interest is not limited to industrialized countries, but also includes oil-exporting countries. Solar energy is one of the largest and most important renewable energy sources currently used in electrical power generation. Photovoltaic (PV) panels can be installed anywhere there is sufficient energy potential in terms of radiation and surface area. This interest has encouraged many investors in building large PV plants to generate electric power, and many small, and medium enterprises have turned to using PV systems. Despite the rapid expansion of PV systems, they have faced significant challenges, including fault detection, in order to raise system efficiency and reduce maintenance cost as well as repair time [2]. With this concern, a range of faults have emerged in PV systems resulting in a partial or total loss of energy productivity [3], [4]. There are common faults in PV systems including ground fault, line-to-line fault, hot spots, bypass mismatch, and electric arc faults [5]. The fault detection procedure is mainly based on modeling and simulation of the entire PV system and real-time measurements of variables. Fault analysis is important in improving the efficiency and reliability of a PV system. However, the traditional current methods used for fault detection and maintenance in PV arrays are still ineffective, labor-intensive and time-consuming [6]. Several studies have addressed the issue of faults in PV systems by proposing algorithms to detect faults in these systems through continuous monitoring of system performance [7].

The method proposed by Firman *et al.* [8] is based on the analysis of data through statistical methods and allows to diagnose or detect the instantaneous decrease in the generated power. Through this, faults that may occur in the system can be identified. An infrared thermal energy analysis technology is developed to detect faults in hot spots [6]. Infrared rays are used to produce sequential thermal images of the PV array. The proposed procedure was simulated for a 100 kW PV plant using the MATLAB/Simulink model. In another study [9], a methodology for faults detection was proposed, it consists of training two artificial neural networks (ANNs). The first ANN is a binary classifier that detects whether there is a fault or not, while the second ANN is a multiclass classifier that detects the fault type. The energy generated by PV systems is highly dependent on weather conditions and is affected by several types of faults, which can lead to severe energy loss during the operation of the system [10]. Therefore, accurate prediction of the PV generated is very important as they contribute to the stability of the energy integration between PV power and the national grid [11]-[13]. Prediction of renewable energy generated is based on real-time monitoring system for solar panels and energy conversion modules.

Significant advances in wireless communication technologies and sensors have enabled designers to use the internet of things (IoT) in monitoring and control systems [14], [15]. The IoT provides a huge amount of data over an internet connection. Humans cannot easily deal with big data especially in real time applications, so there is a need to use artificial intelligence (AI) technology with the IoT [16]. Recently, a number of researches dealt with several machine learning models to predict the behavior and energy production of PV systems to detect faults in combination with real-time data provided by IoT devices [12], [17], [18]. Zhou *et al.* [16] propose a method based on the use of the concepts of the IoT and AI to overcome the current difficulties of the PV energy generation forecasting problem. A hybrid deep learning methodology between a convolutional neural network (CNN) and long-term memory was used to predict PV generation. Another paper [19] presented an intelligent approach that uses two-dimensional CNNs to extract features from two-dimensional measurement generated by PV system data to detect and classify PV system faults. AI algorithms are used to process the big data generated by IoT devices to model fault detection in PV systems. Various types of neural networks [19], [20] and fuzzy logic [2], [7] have been used in faults detection. Recently, deep learning has recently received great research efforts in various fields and applications, including fault detection [21]. The deep learning model is a hierarchical learning structure, in which complex nonlinear functions are used [22]. In an attempt to detect faults in a PV system based on deep learning, aerial images obtained from drones were used. In this case, CNNs are trained to extract high-level features from images and classify faults [23]. The deep learning model was also used to detect and classify six faults in the direct current (DC) side of the PV system. Three electrical indices were used as inputs to a classification model based on a CNN [24].

This paper aims to introduce a deep learning algorithm to detect and locate faults by utilizing the same sensors available for real-time monitoring and control of PV systems. A number of indicators, as inputs to the CNN model, are analyzed using the same IoT devices for real-time monitoring. By training and testing the CNN model on the data from the PV system, faults can be detected and located with high accuracy. The remainder of the paper was arranged as follows: the section 2 presents the common faults in PV systems. The section 3 deals with the design of the implemented PV system for the water pumping station. The section 4 presents the IoT design for PV systems. Section 5 introduces fault detection using deep learning approach. The section 6 provides a discussion of simulation results, while the final section summarizes the conclusion.

2. FAULT DETECTION

Faults detecting in a PV system requires an understanding of the behavior of current/voltage parameters in different environmental conditions. So, a complete simulation package for the PV system under test must be provided, allowing the extraction of parameters for the simulation model of the PV system and real measurements of both electrical and atmospheric variables. For fault detection procedures, reference thresholds are established based on the error between simulation and real-time measurement when the PV system is operating without faults or when there are potential faults [4]. In fact, the process of detecting faults in PV systems has become a software unit that relies primarily on analyzing data generated from the IoT using AI in order to create predictive models for PV components as well as for power transformers.

The faults of PV systems are either on the DC side or on the alternating current (AC) side. Faults that occur on the DC side are categorized into three types: PV array faults, maximum power point tracking (MPPT) module faults, and cabling system faults. When any failure occurs in the MPPT module, the output voltage and output power will decrease. While, most of the faults that may occur in the cable system and power transmission lines will lead to an obvious drop in the output voltage and output power [4], [5]. Common faults in PV panels can be categorized into three main types; physical faults, electrical faults, and environmental faults, as given in Figure 1. Physical faults include PV module damage, PV module cracks, bypass diode damage and degradation. Environmental faults: include shading faults and hotspots faults. The environmental factor is also a cause of faults in PV systems in terms of corrosion, rodent chewing, water ingress, mechanical damage and aging. While, electrical faults include open circuit faults, line-to-line faults, mismatch faults, ground fault, and arc faults. However, the most common faults on the DC side are line-to-line faults, open circuit faults, and shading faults. This paper focuses on fault detection in PV systems resulting from shading. Partial shading occurs when a part of the PV panels is shaded by some obstructions such as trees, buildings, dirt, and clouds. This will lead to power losses and hotspots in the PV modules [6].

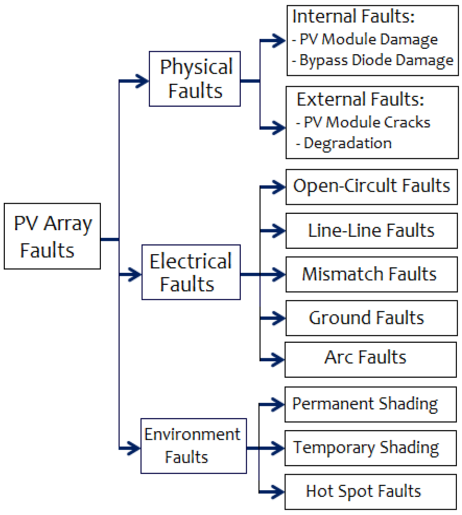


Figure 1. PV array fault classifications

3. PV WATER PUMPING SYSTEM

Iraqis suffer from a significant deterioration in services (especially electricity and water) due to the unstable conditions in Iraq during the past two decades. For example, the water pumping station in Serbasti in Erbil-Northern Iraq operates at a rate of no more than 4 hours per day (due to the lack of electricity in the national network) and provides less than 0.7 cubic meters per household per day, which is less than the internationally approved minimum. Therefore, there was a need to use renewable energy sources, especially PV panels, to avoid interruptions and the great shortage of the national grid. PV energy was used for pumping water in Serbasti-Erbil through a project funded the International Organization for Migration, contributing to the provision of approximately 1.3 cubic meters per day to the family [25]. There are many problems facing such projects in Iraq, represented in the lack of regular maintenance or periodic cleaning of solar panels, especially with a dusty climate. Therefore, the trend was to design a real-time monitoring and fault detection system for the PV panels in this project and to use them in other projects.

Our previous studies [25], [26] dealt with the specifications and data related to the design of the solar power plant and water pumping system in Serbasti. The PV system contains seven parallel strings, each string consists of 20 PV modules connected in series as illustrated in Figure 2. The total number of solar panels is 140 panels (240 Watts) to implement an efficient solar system with a capacity of 35,000 Watts.

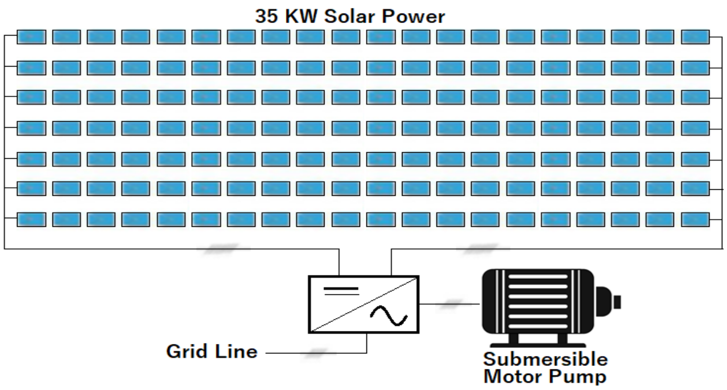


Figure 2. Solar panels distribution

4. IoT FOR PV SYSTEMS

IoT technologies allow computerized and embedded devices to be interconnected over the internet, and enable them to send and receive data wirelessly. Data generated from IoT sensors along with AI algorithms can also be used in PV systems in several areas, including: i) enhancing system efficiency by improving the efficiency of renewable energy, ii) optimizing the consumption of renewable energy sources through intelligent load management, and iii) predicting faults that may occur in the PV system, which enhances maintenance efforts and increases system reliability. Therefore, by applying AI algorithms to data generated by IoT devices, it becomes possible to analyze data patterns to discover and identify various faults in PV systems.

4.1. IoT sensors

In PV systems, several sensors used to sense and collect data, for further processing to generate the necessary control signals. The following sensors are commonly used: i) current and voltage sensors are used to measure the basic performance of the device, ii) light sensors light dependent resistor (LDR) is used to measure solar radiation, and iii) temperature and humidity sensors are used to measure the amount of humidity and temperature as they have a direct impact on the performance of PV panels. Each PV module has set of sensors connected to an embedded microcontroller to measure voltage, current, temperature, and irradiation, as illustrated in Figure 3. The measured data from PV modules will be serially transferred to the WiFi microcontroller, and then to the main controller for further analysis and decision. The operator can access real-time scanned data and decisions directly through a smart phone or a personal computer connected to the internet.

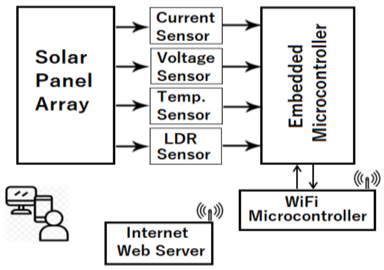


Figure 3. Microcontroller-based PV module

4.2. Data driven faults detection

Fault detecting is one of the most important challenges facing PV systems, as it helps to speed up maintenance procedures and restore the system to work with high efficiency. Fault detection methods require large amounts of PV data for training and testing purposes. This data is usually collected under certain conditions, and may change with the weather in each season. It is therefore necessary to update fault detection algorithms to be smart and self-learning. The proposed fault detection approach uses real-time data obtained from the PV system. There is no need to build a measurement system to collect the required PV data, because it uses the same sensors that are available in the real-time monitoring module of the PV system. Four variables (current, voltage, operating temperature, and solar radiation) are obtained directly through IoT sensors.

5. FAULTS DETECTION USING DEEP LEARNING

Deep learning is a type of machine learning that relies primarily on ANSs to handle large amounts of data. Deep learning techniques can analyze images, videos, and unstructured data in straightforward ways. It uses multi-layered neural networks to represent nonlinear relationships between input variables in order to reach the desired goal. Therefore, building deep learning algorithms depends on the availability of huge amounts of data to generate acceptable results with relatively little need for human intervention. There are many deep learning algorithms used in error detection applications. In this paper, GoogLeNet is used to implement an intelligent approach to detect faults, caused by shading, in a water pump PV system. GoogLeNet is a multi-layer CNN containing ready-made code that can be used with some modifications to suit the proposed methodology. Figure 4 shows the general outline of the implemented deep learning approach, and includes the following steps:

- Convert the data generated from IoT sensors (time series signals) for each PV into a 2D image.
- For each PV string, transform 2D images to 3D images (scalogram) to be processed by CNN.

- Load the image created in the scalogram for each string to the deep learning algorithm.
- Deep learning tries to find a feature extraction after finding a common feature and then defines the feature by giving an average value of each category.
- When a new image is received, the average value of the new image is calculated and then rotated to a category close to the new image classification method to determine the fault location.

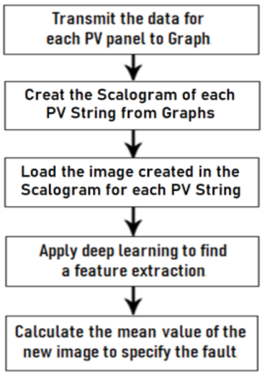


Figure 4. Deep learning algorithm

6. RESULTS AND DISCUSSION

MATLAB/Simulink was used to simulate several experimental tests on the DC side of the PV system to evaluate the implemented fault detection approach. Figure 5 shows the effect of solar radiation on the IV and PV curves of the simulated PV system at an ambient temperature of 25 °C and different irradiance levels (1,000, 500, and 100) W/m^2. It is shown that the generated current as well as the power decreases as the level of radiation decreases.

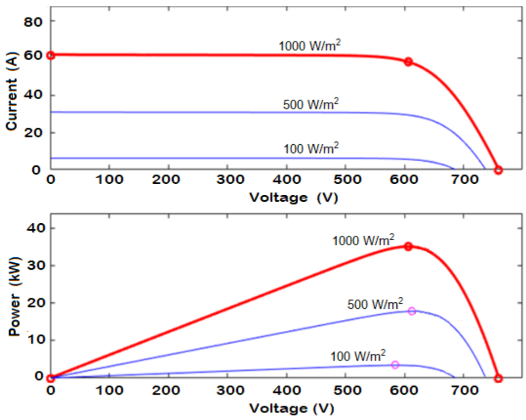
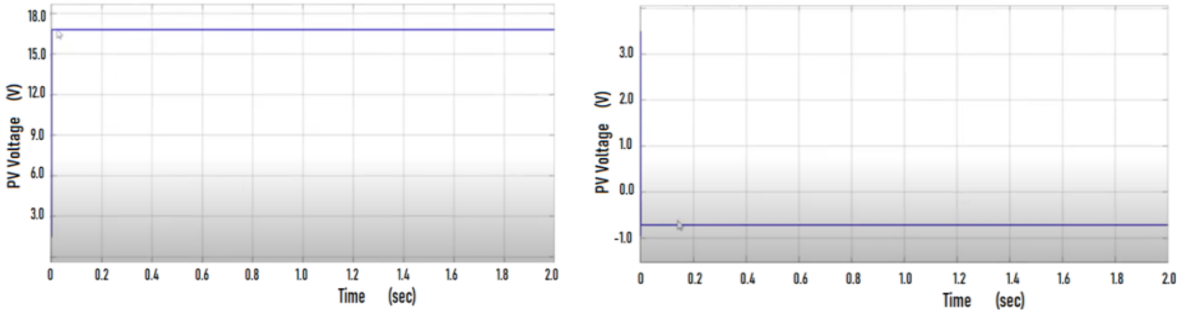


Figure 5. Characteristics of the PV system with radiation changes

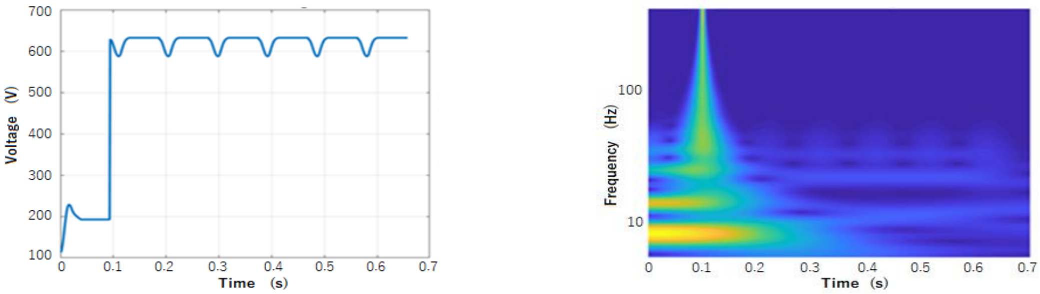
In order to identify and locate shading faults in the PV system, a number of tests were conducted, and one of these tests was faults-free, while the other tests included shading faults. All PV panels in the implemented system were connected to static radiation 1,000 W/m^2 and only one panel to 50 W/m^2 for the purpose of representing partial shading or shading due to dust. To detect any fault in the PV system, the same current and voltage signals of the real-time monitoring module were used. Figure 6 shows the output voltage of a normal PV panel as well as when it is faulty. In Figure 6(a) the radiation is 1,000 W/m^2, while in Figure 6(b) it is shaded with a radiation of 50 W/m^2. It is clear that the output voltage drops to -0.8 V, as in Figure 6(b), while the modules with a radiation of 1,000 W/m^2 maintain the same voltage. The output voltage gives a clear indication of the faulty unit. This concept has been used in deep learning approach to discover faults related to shading issue that may occur in any PV panel.



(a) (b)

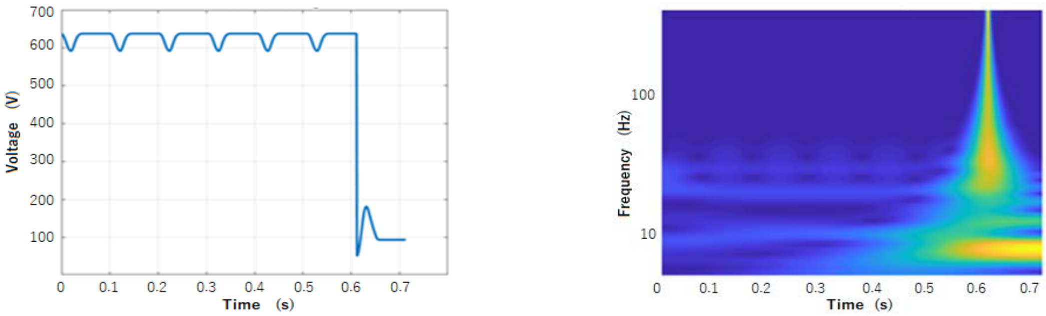
Figure 6. Output voltage of a normal and a faulty PV panel (a) normal, at 1,000 W/m^2 and (b) faulty, at 50 W/m^2

The effects of shading errors for PV panels are clearly visible in the scalograms indicated in Figures 7 and 8. The irradiation voltage of PV1 is shown in Figure 7(a), while the scalogram is shown in Figure 7(b). The irradiation voltage of PV2 is given in Figure 8(a), while its scalogram is illustrated in Figure 8(b). It is evident that the tone and color concentration in the radiographs are related to the faults of the shaded PV panel. Classification in deep learning is the process of classifying a given data set into different classes depending on the classification of features from seven PV strings in the implemented simulation design. The 100 sets of data for each PV category are divided into two parts; 70% of this data set is used for the learning phase and the remaining 30% is used to test the accuracy of our approach.



(a) (b)

Figure 7. PV1 of (a) irradiation voltage and (b) irradiation scalogram



(a) (b)

Figure 8. PV7 of (a) irradiation voltage and (b) irradiation scalogram

Figure 9 shows only ten of the 100 images of the first string (string #1), as well as 10 images of the string #7. The difference in color concentration and different tone can be observed according to the faulty panel. The overall performance of the proposed fault detection algorithm is shown in Figure 10. The given plots show how the accuracy and loss for both the training and validation sets vary with respect to the number of iterations. It can be seen that the increase in the number of iterations and epochs tends to show a gradual increase in both training accuracy and validation. Also, it can be seen that the average overall training accuracy reaches 100% after 100 iterations. This definitely leads to a loss function reduction due to the accelerated learning ability of the network. The obtained results indicate that the proposed deep learning approach increases the accuracy of faults detection and reduces the loss as much as possible. The overall validation accuracy of the trained network was observed to be almost 100% which is also evident from the confusion matrix given in Figure 11. The confusion matrix used 30% of the available data to validate the search methodology and test the accuracy of the faults detection algorithm.

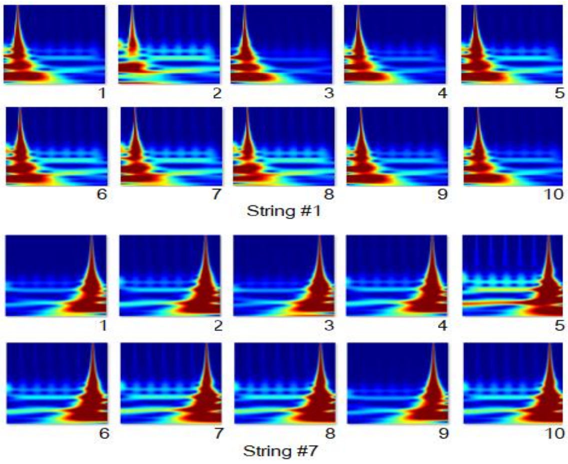


Figure 9. Scalogram images for strings #1 and #7

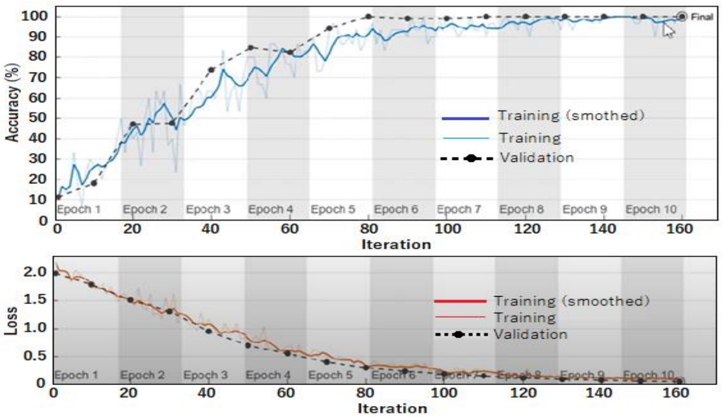


Figure 10. Accuracy and loss achieved when using GoogLeNet

Output Classes

PV1	30 14.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
PV2	0 0.0%	30 14.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
PV3	0 0.0%	0 0.0%	30 14.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
PV4	0 0.0%	0 0.0%	0 0.0%	30 14.3%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
PV5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	30 14.3%	0 0.0%	0 0.0%	100% 0.0%
PV6	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	30 14.3%	0 0.0%	100% 0.0%
PV7	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	30 14.3%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%
	PV1	PV2	PV3	PV4	PV5	PV6	PV7	

Target Class

Figure 11. Confusion matrix of pre trained network

7. CONCLUSION

The paper dealt with the use of IoT and deep learning techniques in detecting faults caused by shading in a PV water pumping system in Erbil-Northern Iraq. Four sensors were adopted to measure current, voltage, temperature and solar radiation, which are the same sensors used in the PV system. The implemented fault detection algorithm is mainly based on simulation of the PV system as well as real-time measurements from sensors. Many indicators are analyzed and compared from PV system simulation and real-time measurements. The deep learning approach uses data obtained from the IoT to detect and locate faults. The simulation results showed that using deep learning was successful in detecting and identifying faults. The results also showed the accuracy of fault detection compared to the traditional methods used. The proposed approach shows 100% efficiency in detecting shading faults which is one of the main challenges facing PV systems in Iraq.

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