Advancements and Challenges: A Comprehensive Review of Machine Learning and IoT-enabled Approaches for Fault Detection and Mitigation in Solar Photovoltaic Systems

[1].Chandrashekar.B.M., [2].Dr. Hannah Jessie Rani. R., [3].Dr. G. Ezhilarasan, [4].Dr.M.V.Panduranga Rao,[5]. Dr. Ashok Kumar P.S.,

1Research scholar, EEE, FET-Jain (Deemed-to-be-University), Bangaluru, Karnataka, India.
2Assistant Professor in EEE, FET, Jain (Deemed-to-be-University), Bangaluru, Karnataka, India.
3Professor in EEE, FET Jain (Deemed-to-be-University), Bangaluru, Karnataka, India.
4 Professor ,CSE, FET-Jain (Deemed-to-be-University), Bangaluru, Karnataka, India.
5Professor in CSE, ACS college of engineering, Kambihalli, Bangaluru, Karnataka, India.

Abstract
This extensive analysis explores the dynamic convergence of machine learning (ML) and the Internet of Things (IoT) within the domain of solar photovoltaic (PV) systems. It reveals a progression of developments, obstacles, and prospective goals. By examining the historical progression of solar PV technology, the text emphasises the critical significance of ML and the IoT in transforming approaches to fault detection and mitigation. The paper clarifies how ML techniques improve accuracy and flexibility, going from rule-based systems to the modern fusion of predictive analytics and adaptive control. The paper emphasises the critical significance of integrating ML and IoT methodologies, showcasing their capacity to develop robust, self-educating solar PV systems. Security, scalability, and interoperability challenges are analysed, with an emphasis on the necessity for resilient solutions that guarantee the dependability of the system. A review of prospective developments emphasises the following: enhancing the precision of ML algorithms, incorporating edge computing to enable real-time responsiveness, and guaranteeing the comprehensibility of artificial intelligence models. It is suggested that blockchain technology could be potentially integrated into interconnected systems to protect them. This investigation ultimately functions as a reference point for scholars and professionals, envisioning a forthcoming era in which intelligent PV systems, enabled by the integration of ML and IoT technologies, make a substantial contribution to the efficacy and sustainability of renewable energy.

Keywords: Fault Detection, Fault Diagnosis, Internet of things (IOT), Machine learning algorithms(ML)

1. Introduction

L As the world grapples with the issues of climate change and the need for sustainable energy solutions, the integration of renewable energy sources into our power systems has become a key priority. Solar PV systems stand out as a possible option for capturing the sun's endless energy among these renewable sources [1]. However, effective utilisation and maintenance of solar PV systems present daunting obstacles, the most significant of which is the identification and mitigation of defects that might impair system performance. Traditionally, fault detection approaches in solar PV systems have relied on rule-based systems and traditional control mechanisms. While these techniques have yielded useful insights into system behaviour, they frequently fall short of dealing with the complexity and unpredictability inherent in real-world operating settings [2]. The convergence of ML and the IoT has emerged as a revolutionary force in recent years, providing creative solutions to improve the fault detection and mitigation capabilities of solar PV systems.

The search of effective defect detection and mitigation solutions in solar PV systems is not new. Traditional engineering principles-based procedures have long been used to assure the dependability and lifespan of these systems. However, due to the dynamic and non-linear nature of solar PV systems, as well as the rising scale and complexity of installations, a paradigm shift in how faults are discovered and managed is required. This is where the convergence of ML and IoT technologies comes into play.

1.1. Motivation for Fault Detection and Mitigation in Solar Photovoltaic Systems

The reasons for improving problem detection and mitigation in solar PV systems are several. For starters, the economic consequences of system unavailability or underperformance are significant. Any variation from ideal operation leads in energy losses and reduced income production, which has a direct influence on the return on investment for solar PV plants. Second, errors can hasten equipment degradation, resulting in higher maintenance costs and a shorter system lifespan. Furthermore, in grid-connected systems, malfunctions can have a domino impact on the overall stability and dependability of the electrical grid.

The environmental effect of inadequate solar PV system performance must also be considered. Solar energy's fundamental attractiveness is its green and sustainable character, and any inefficiency in utilising this energy source reduces the total environmental advantages. As the globe shifts towards renewable energy adoption as a method of combating climate change, maintaining the optimal operation of solar PV installations becomes critical.

1.2. Importance of Machine Learning and IoT Integration

The incorporation of ML and IoT technologies into problem detection and mitigation tactics provides solar PV systems with a new degree of intelligence and flexibility. ML, with its capacity to recognise patterns and anticipate outcomes from data, represents a shift from rule-based techniques. It enables the creation of models capable of learning and adapting to the ever-changing circumstances of solar PV systems, making them more resilient in detecting and mitigating errors [3]. At the same time, the IoTs has transformed the way we acquire and handle data from solar PV systems. A lot of real-time data is now available due to the growth of sensors and communication devices installed in PV systems. When used correctly, this data offers the input required for ML algorithms to make educated judgements and predictions. The combination of these two technologies has the potential to usher in a new age of smart and self-adaptive solar PV systems [4].

Historically, deterministic algorithms and rule-based systems were widely used in defect detection in solar PV systems. While these approaches provide useful insights, they are unable to account for the inherent unpredictability and complexity of solar energy output. Early techniques to defect detection were frequently threshold-based, with departures from anticipated performance triggering alerts. These techniques, however, were insufficient for capturing subtle and dynamic fault conditions [5]. Researchers have investigated increasingly complex methods in recent decades, such as model-based approaches and enhanced control tactics. While these systems displayed better fault detection accuracy, they frequently encountered computational complexity and scalability problems. Furthermore, they have difficulty adapting to the different and dynamic working circumstances of solar PV systems in the field.

Traditional techniques' inadequacies highlight the need for a paradigm shift in fault detection and mitigation solutions. ML, with its capacity to extract meaningful patterns from massive datasets, and the IoTs, which enables real-time data capture and transmission, have emerged as game-changing technologies with the potential to successfully overcome these constraints.

1.3. Scope of the Review

The main goal of this paper is to give a thorough analysis of the present status of ML and IoT applications in identifying defects and mitigation in solar PV systems. It hopes to illustrate the strengths and limits of diverse approaches, highlight successful case studies, and identify new trends and difficulties by synthesising current work. The scope is broad, ranging from the fundamental principles of ML and IoT integration to the actual use of these technologies in real-world solar PV installations. In the following parts, we will look at the history of solar PV systems, the evolution of defect detection algorithms, and cutting-edge ML applications in solar energy. We will also investigate the integration of IoT technologies for improved monitoring and control, laying the groundwork for further talks on the field's integrated methodologies, applications, difficulties, and future perspectives.

This study is intended to be a useful resource for academics, practitioners, and policymakers working at the convergence of renewable energy and advanced technology. As we begin this journey, the complex interaction between ML and the IoTs, suggesting a paradigm shift in how we handle the difficulties of fault detection and mitigation in solar PV systems.

2. Literature Review

This thorough review's literature analysis takes the reader on an intellectual journey across the broad and dynamic terrain of ML and IoT applications in fault detection and mitigation within solar PV systems. We weave the vast tapestry of academic contributions that form the foundation of our understanding in this part, showing the important research routes, seminal publications, and contemporary viewpoints that characterise this multidisciplinary area.

2.1. Historical Development of Solar Photovoltaic Systems

The history of solar PV systems is one of constant innovation, technical advances, and an increasing dedication to capturing clean and sustainable energy. This section examines the evolution of solar PV technology, from early discoveries to modern improvements. Understanding the historical backdrop provides insights into the trajectory of solar PV systems, laying the groundwork for a more in-depth discussion of defect detection and mitigation in subsequent parts.

i. **Early Foundations and Photovoltaic Discoveries**: The groundwork for solar PV technology was created in the 19th century, with critical discoveries advancing our understanding of the photovoltaic effect. Alexandre Edmond Becquerel discovered the photovoltaic effect in a cell made up of metal electrodes in a conducting fluid in 1839, offering the first view of sunshine being directly converted into energy [6]. This revolutionary finding laid the theoretical framework for the use of solar energy.

ii. **Maturation of Solar PV Technology: 1950s-1990s:** Solar PV technology gradually matured following 1954. Solar cells progressed from single-crystal silicon to polycrystalline and thin-film technology, broadening their application range. Solar PV systems found niche applications in space exploration at this time, powering satellites and space probes [7]. During this time, notable developments included the discovery of amorphous silicon solar cells, which cleared the way for flexible and lightweight solar panels. The first solar photovoltaic research centres were established in the 1980s, boosting collaboration between academics and industry [8]. These coordinated efforts resulted in higher efficiency and lower prices, making solar PV more economically viable.

iii. **Growth and Global Adoption: 21st Century:** The 21st century was a historical era for solar PV systems, with phenomenal growth and broad use. Material science advancements, improved manufacturing techniques, and government incentives fuelled the solar industry's growth. China has emerged as a prominent player in solar panel manufacture, resulting in economies of scale and additional cost reduction [9]. Solar cell technology advancements, such as the invention of perovskite solar cells, opened new avenues for higher efficiency and flexibility.

2.2. Evolution of Fault Detection and Mitigation Techniques

Currently, the existing PV protection standards aim to safeguard PV arrays against three primary types of faults: line-line (LL), line-ground (LG), and arc faults. Figure 1 visually depicts the many potential electrical faults that may arise within the component of a PV system.

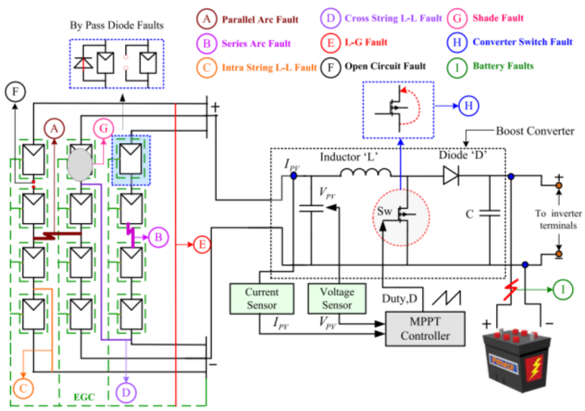

Figure 1. Potential Electrical Faults in PV System [10]

Notwithstanding these obstacles, PV arrays remain susceptible to a multitude of additional potential complications. These encompass open circuit (OC) faults, degradation issues, bypass diode breakdowns, shading faults, hotspots, and connection malfunctions. To ensure dependable protection, numerous novel fault detection strategies have been proposed in recent times, in addition to well-established methodologies [10]. Additionally, it is worth noting that the fundamental approach of each proposed fault identification technique differs significantly in terms of conceptual variation. However, it is unfortunate that these methodologies have not been methodically classified and evaluated for their effectiveness in the current corpus of literature. Hence, it is critical to undertake a comprehensive inquiry to classify, evaluate, and assess the efficacy of these sophisticated defect detection methodologies. There are two primary categories into which fault detection and classification approaches can be classified: electrical-based methods (EBMs) and visual and thermal methods (VTMs) as show in Figure 2 [11]. The fault classification phase concludes the framework for defect detection and mitigation. For PV systems, numerous classification techniques based on machine learning have been developed. For instance, an innovative approach utilising Artificial Neural Networks (ANN) was introduced by researchers. This methodology integrates two discrete algorithms. The initial algorithm identifies six distinct fault categories through threshold detection. In contrast, the second algorithm detects short circuits within PV arrays by utilising an ANN.

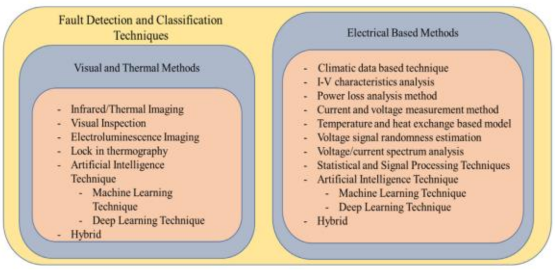

Figure 2. Fault Detection Techniques

In general, defect detection and mitigation procedures consist of two fundamental phases: the selection and extraction of features, and the classification of faults [12]. In the preliminary stage, the objective is to discern the most relevant and adaptable characteristics from the data at hand. Principal Component Analysis (PCA) is widely used as the prevalent approach for feature extraction. However, in specific instances involving nonlinear systems, PCA demonstrates less-than-ideal defect classification performance, which is primarily attributable to its underlying assumption of linearity [13].

At present, a significant proportion of PV systems integrate a monitoring infrastructure that sustains an ongoing database with abundant historical data [14]. Artificial Intelligence (AI) techniques rely on data, and the current abundance of large datasets in PV systems has led to a surge in research activities in this domain. Approaches and algorithms based on ML are recommended [15]. These methodologies entail training the model with historical data to predict and classify faults. A convolutional neural network (CNN) is utilised in reference [16] to address the challenge of defective classification with the intention of improving the adaptability and dependability of the analysis of images of aerial PV modules. In [17], an ensemble learning technique known as Random Forest (RF) is suggested for the identification and correction of faults in PV arrays. The objective is to identify and categorize faults in PV arrays by integrating various learning algorithms, thereby attaining an enhanced diagnostic performance.

3. Machine Learning Techniques in Fault Detection

The integration of ML methodologies into solar PV fault detection has brought about a significant paradigm shift in the approach taken to detect and resolve anomalies. This segment offers a comprehensive examination of diverse machine learning algorithms, classified as supervised or unsupervised learning methods, including reinforcement learning. It emphasises the functions, advantages, and practical implementations of these algorithms in improving the dependability and efficiency of solar photovoltaic installations.

The researchers conducted a comparative analysis in [18] to assess the anomaly detection capabilities of three ML models. By employing data collected from operational PV power plants in India, the objective of this analysis was to establish correlations among a range of plant internal and external parameters. The results of the research demonstrated that the "auto-encoder and long short-term memory" (AE-LSTM) combination demonstrated efficient capabilities in detecting anomalies and differentiating healthy signals. An alternative approach to fault diagnosis in PV modules, separate from signal processing, was presented in the references [19, 20]. The authors suggested fault classification using infrared thermography images (IRT) as the foundation. Recent research by the authors includes the presentation of an automated fault detection methodology. This methodology entails the utilisation of supervised machine learning in conjunction with the examination of texture features. The suggested approach utilises fuzzy edge detection to determine the orientation of modules displaying anomalies and IRT to identify anomalies in PVM. The identification of defects and categorization of four distinct patterns (Block, Patchwork, Single, and String) linked to defective modules using IR images were accomplished by the researchers in reference [21] using deep neural networks (DNN) and SVM. The study did not undertake a more comprehensive categorization of distinct PV degradation modes, including but not limited to chipping, shadowing, and stains, despite achieving an approximate 89% accuracy rate in classifying the four defect categories. The efficacy of employing CNN in conjunction with IR images to identify anomalies in PV panels has been established. However, further investigation is required to determine whether these ML methods can be utilised to classify different varieties of anomalies.

An increasing number of PV systems are currently being incorporated with monitoring systems, resulting in the production of considerable volumes of data, which are widely known as "Big Data" [22]. The necessity for the implementation of advanced data mining methods has been emphasised by the prevalence of big data in PV systems. These methods are of the utmost importance in precisely detecting faults and improving the overall effectiveness of the system. A novel framework for defect detection was introduced in reference [23], which utilised an intelligent approach. The integration of a probabilistic neural network (PNN), a non-linear ML technique useful for unsupervised as well as supervised learning tasks, was crucial to this framework. The principal aim of the endeavour was to discern and categorise defects, dividing them into discernible fault categories. The datasets utilised for analysis comprised examples from both typical PV operations and PV functioning under default conditions, with a particular focus on the winter season.

A comprehensive analysis of the current body of literature indicates that machine learning algorithms, specifically CNN and ANN, are the prevailing methods employed for defect detection and classification in PV systems. The performance of these models is significantly influenced by PV imagery, which includes EL (Electroluminescence), RGB, and IR images, in addition to PV-specific attributes, which function as inputs. The depicted configuration can be found in Figure 3. Table 1 provides the comparative analysis of ML techniques applied to PV fault detection and classification.

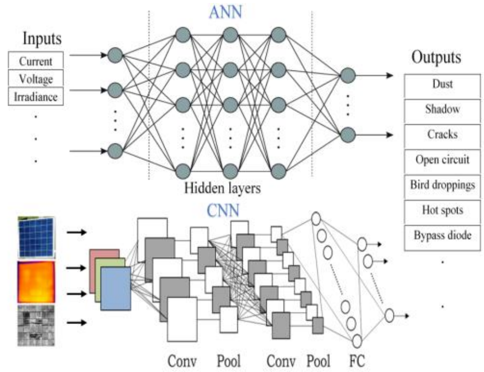

Figure 3. PV System Fault Detection and Classification Architecture [24]

Table 1. Comparative Analysis of ML Techniques

Reference	Technique	Objective's	Remarks
[20]	Ensemble algorithm	Fault detection and classification	Only specific categories of faults are taken into account
[21]	DNN	Fault detection	Insufficient precision.
[23]	PNN	Fault detection and classification	Inadequate training and testing data
[25]	ANN	Fault detection and classification	Extensive training duration

[26]	PCA	Fault detection and classification	Only specific categories of faults are taken into account

3.1. Challenges and Considerations in Machine Learning for Fault Detection

Although ML techniques provide substantial progress in fault detection, there are various challenges and factors that warrant careful consideration.

i. **Data Quality and Quantity:** The efficacy of ML models is significantly influenced by both the calibre and volume of operational data. The model's capacity to generalise to a wide range of defect scenarios could be compromised by unreliable or conflicting data [27].

ii. **Model Interpretability:** Trust and decision-making depend on the comprehension of how and why a model generates predictions. Maintaining the interpretability of ML models for fault detection remains a persistent obstacle [28].

iii. **Real-time Processing:** Due to the real-time operation of solar PV systems, fault detection mechanisms must be prompt and effective. Processing speed and power are crucial factors to take into account when deploying machine learning models for real-time fault detection [29].

4. IoT-enabled Monitoring and Control

The advent of real-time monitoring, adaptive control, and increased efficiency in solar PV systems has been facilitated by the incorporation of the IoT. This section delves into the complex relationship between IoT technologies and solar PV installations. It clarifies the ways in which cyber-physical systems, sensor networks, data acquisition, and communication protocols all contribute to improved monitoring and control capabilities.

The IoTs enables the interchange of information and communication between a wide variety of devices, systems, and services. Recently, IoT applications for remote sensing and the monitoring of PV systems have been investigated [30]. This investigation is motivated by the need for enhanced defect diagnostics and prognostics within the industry. In a previous study [31], the identification of sensor malfunctions in grid connected PV systems was addressed. The authors additionally proposed in that study the ideal placement of current and voltage sensors to reduce the financial burden caused by the addition of unnecessary sensory devices. As per the findings stated in the source [32], an advanced IoTs system achieves automation and adaptability through the application of artificial intelligence methodologies. The three primary tiers of the IoT framework are the application layer, the network layer, and the perception or object layer. When considering large-scale photovoltaic (PV) installations that consist of multiple inverters, sensors, and protective devices, one can adopt a more economical approach by integrating all communication capabilities into a single hardware unit [33], rather than utilising numerous separate communication devices. As a result, the use of high-speed communication technologies facilitates real-time monitoring and control, which is crucial for the efficient management of distributed renewable generation systems. The experimental configuration consists of a multitude of sensors that are specifically engineered to quantify a wide range of parameters. These parameters include internal combustion engine (AC) current and DC voltage, solar irradiance, DC-current and current from PV strings and arrays, air temperature, cell or module temperature, wind speed, relative humidity, and cloud cover [34]. To guarantee accuracy and dependability in measurements, it is critical that the sensors undergo rigorous calibration and conditioning in strict adherence to globally recognised standards. A depiction of an intelligent photovoltaic (PV) monitoring system utilizing Internet of Things (IoT) technology is illustrated in Figure 4.

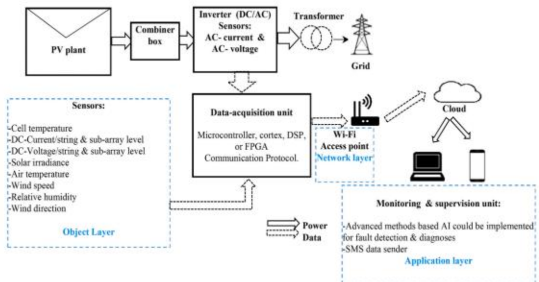

Figure 4. IoT Based PV system [34]

A remote monitoring system and control unit for PV plants were created in reference [35]. This system enables preventive maintenance, historical analysis of PV plant performance, real-time monitoring, and fault diagnosis using the extreme learning technique. Additionally, a webpage for a PV monitoring centre has been established, allowing the transmission of warning notifications to users via email in the event of a PV array fault. A data-logging system that was recently devised for the purpose of monitoring PV systems via mobile and web interfaces was introduced with reference to [36]. As per the developers, the cost of this monitoring system is significantly diminished in comparison to currently available commercial alternatives, thereby facilitating accurate remote monitoring at an economically viable price. In reference [37], a fault detection and identification system for intelligent PV applications was developed. The prototype that was created, which included a simple identification algorithm, was subjected to experimental validation. The outcomes showcased the efficacy of the system in detecting a range of malfunctions, such as open-circuits, dust accumulation, short-circuits, and shading effects.

The application of IoTs technology for the remote monitoring of PV systems has become prevalent in residential environments, specifically for PV installations on a modest scale. These systems frequently exhibit reduced expenses in comparison to their commercially available alternatives. However, there may be some degree of constraint on their efficacy. In addition, it should be noted that commercially available monitoring systems, despite their higher cost, struggle to fulfil the varied needs of consumers worldwide.

4.1. Challenges and Considerations in IoT-enabled Monitoring and Control

The incorporation of the IoTs into solar PV system monitoring and control presents a variety of advantages, but also substantial obstacles and factors to be taken into account. Comprehension and resolution of these obstacles are vital for the effective deployment and long-term viability of solar installations enabled by the Internet of Things.

i. **Data Security and Privacy:** Data transmission and storage may be susceptible to potential vulnerabilities due to the interconnected nature of IoT devices. The implementation of robust encryption, secure authentication mechanisms, and the adoption of security protocols that adhere to industry standards are critical in order to protect sensitive data and guarantee privacy [38].

ii. **Device Authentication:** IoT device unauthorised access presents a security risk. Ensuring the security of access credentials, implementing robust device authentication mechanisms, and employing secure key management are critical preventive measures against unauthorised access [39].

iii. **Managing Data Volume:** The proliferation of interconnected devices produces enormous volumes of data that may present difficulties in terms of management and processing. Scalability can be managed with the assistance of scalable architecture implementation, periphery computing solution integration, and data transmission optimisation [40].

iv. **Diverse Devices and Protocols:** Diverse manufacturers produce IoT devices, each employing a unique set of communication protocols. Interoperability is improved by adopting standardised communication protocols, such as MQTT or CoAP, and ensuring device compatibility through adherence to common standards [41].

v. **Integration with Existing Systems:** It can be difficult to integrate IoT systems with pre-existing infrastructure. Integration is facilitated by employing middleware solutions, integrating open APIs, and performing exhaustive compatibility assessments throughout the system design process [42].

5. Combined Approaches: Case Studies and Successful Implementations

The integration of ML and the IoTs represents a breakthrough collaboration in solar PV systems, surpassing conventional approaches to monitoring and control. This segment delves into the seamless integration of ML algorithms with IoTs technologies, elucidating the complex mechanisms that drive solar PV installation optimisation, fault detection, and adaptive control to unprecedented levels.

However, to achieve successful integration of ML and the IoTs in solar PV systems, a few prerequisites must be meticulously examined. Prior to anything else, it is critical to establish a resilient and interconnected IoTs framework, consisting of a network of sensors that can gather data in real-time throughout the photovoltaic installation. A wide range of parameters, including temperature, irradiance, voltage, and current, ought to be captured by these sensors. In addition, the establishment of a dependable communication framework that employs standardised protocols is critical to enable smooth data transmission between devices and the central processing systems. Moreover, the implementation of edge computing solutions has the potential to optimise data analytics by decreasing latency for time-critical applications and augmenting processing speed and efficiency. For training and validation purposes, prior to implementing ML algorithms, an exhaustive and clean dataset that is representative of both normal and fault conditions is required. Furthermore, it is critical to prioritise the implementation of security protocols, such as encryption, authentication, and compliance with privacy standards, to ensure the confidentiality and integrity of data exchanged within the Internet of Things ecosystem. To optimise defect detection, adaptive control, and overall system resilience, it is imperative that domain experts, data scientists, and system engineers work together in concert to synchronise machine learning models with the unique specifications of the solar PV system. This synergistic and efficient integration guarantees the success of the project.

5.1. Photovoltaic Agricultural Internet of Things

The Photovoltaic Agricultural of IoTs signifies the amalgamation of IoTs implementations in the agricultural domain with PV technology, a form of renewable energy. PV technology converts solar energy into electrical energy, providing an environmentally beneficial and sustainable power solution. Through the integration of IoT, conventional farming methods are revolutionised through the implementation of a network of interconnected devices that gather, observe, and evaluate data to enhance agricultural procedures [43]. A representation of an ecosystem illustrating the integration of Photovoltaic Agricultural IoTs in smart farming is depicted in Figure 5.

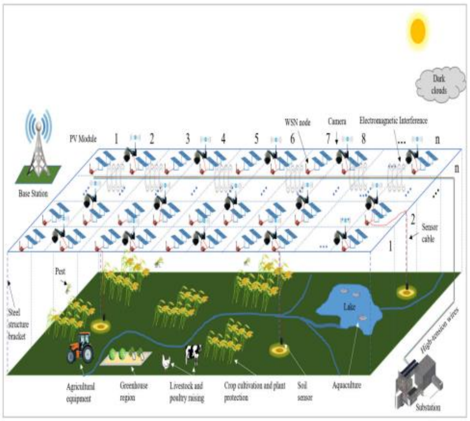

Figure 5. Ecosystem of Photovoltaic Agricultural IoTs [44].

Solar panels are strategically positioned throughout agricultural regions to produce electrical energy using solar radiation. Following generation, the generated energy is utilised to power an assortment of IoT devices, including sensors, actuators, and smart controllers. These devices enable the continuous monitoring of a wide range of agricultural parameters in real-time, encompassing soil moisture, temperature, humidity, and crop well-being. By means of the IoT network, the gathered data is transmitted to a centralised control system, enabling producers to implement precision agriculture techniques and make well-informed decisions.

5.2. Integrated Approach for Generating Renewable Energy Resources

Innovative in nature, the Hybrid Artificial Intelligence (AI) and IoTs model to produce renewable energy resources attempts to meet the increasing demand for sustainable energy solutions. By integrating AI algorithms with IoT technology, this model aims to optimise renewable energy systems and increase their efficiency. Within this architecture, IoT devices are deployed strategically across solar panels. These instruments gather data in real-time regarding energy production, consumption, and environmental conditions. Following that, the data is inputted into an AI system, which optimises resource utilisation, analyses patterns, and predicts energy demand using ML algorithms. The decision-making process is significantly influenced by the AI component of the model, which dynamically modifies energy production in accordance with data collected from IoT sensors. For example, if the AI identifies an upsurge in energy demand, it may direct the system to augment the generation of renewable energy or optimise the allocation of resources [45]. Likewise, when energy generation is hindered by unfavourable weather conditions or periods of low demand, the AI has the capability to adjust the system to optimise energy storage solutions and minimise waste. The research paper referenced as [46] presents a novel predictive model that utilises an Adaptive Neuro-Fuzzy Inference System (ANFIS) and an ANN to forecast PV generation. The proposed forecast model is trained using historical data, and its results are verified and compared by analysing a dataset obtained from a photovoltaic power generation station.

The study cited as [47] examined a variety of machine learning models that were designed to forecast the performance and energy output of a PV system in real time (nowcasting). In conjunction with data from IoTs environmental devices, this analysis was performed. The accuracy of output power predictions was explicitly evaluated by the authors through the utilisation of handcrafted features across a range of temporal contexts. Furthermore, they investigated deep learning methodologies to conduct a comparative assessment of the efficacy of analytic photovoltaic system models. In determining performance, error metrics and learning time were utilised. The dataset employed in this study consisted of empirical data and ambient data pertaining to energy production. The aforementioned information was gathered by a photovoltaic system that was IoT-enabled. It is worth mentioning that this system was developed as a component of the Opera Digital Platform within the UniVer Project, an initiative that has been in operation at the University of Jaén in Spain for the past two decades.

5.3.Future Goals: Integration of ML and IoT

Within the domain of solar PV systems, the amalgamation of ML and the IoT signifies a paradigm shift; forthcoming objectives revolve around augmenting the functionalities and practical implementations of these integrated methodologies. The goal of the convergence of ML and IoT is to develop solar PV systems that are intelligent, self-learning, and capable of defect mitigation and real-time adaptation. Subsequent advancements will centre on the optimisation of ML algorithms to augment predictive analytics, thereby facilitating more precise prognostications of system performance and potential malfunctions. Moreover, the incorporation of edge computing into architectures of the IoTs will enable processing at the periphery, which will decrease latency and enable more rapid responses to dynamic conditions. The continuous endeavour to incorporate explainable AI into ML models will guarantee transparency and interpretability, which are fundamental for establishing confidence in the decision-making procedures. In addition, the integration of blockchain technology has the potential to bolster the level of security achieved in data transactions conducted within interconnected solar PV networks. With the progression of these technologies, forthcoming solar PV installations are anticipated to be robust, versatile, and exceptionally efficient, thereby making a substantial contribution to the sustainable energy domain.

6. Conclusion

This comprehensive review navigated the intricate intersection of ML and the IoT in the context of solar PV systems, unravelling a tapestry of advancements, challenges, and future trajectories. The evolution of fault detection and mitigation techniques demonstrated a remarkable journey from traditional approaches to the symbiotic integration of ML algorithms and IoT technologies. The historical development of solar PV systems laid the groundwork, with ML and IoT emerging as powerful tools to address the inherent challenges of fault detection in this dynamic and critical domain of renewable energy. The development of ML techniques, such as supervised and unsupervised learning, resulted in a significant improvement in the accuracy of fault detection by providing the ability to predict outcomes and the flexibility to adjust to dynamic circumstances. Simultaneously, real-time data streams were introduced through IoT-enabled monitoring and control, which facilitated adaptive responses and created opportunities for remote management and predictive maintenance. The significance of integrated ML and IoT methodologies was underscored in the review. By integrating secure communication protocols, adaptive control, predictive analytics, and self-learning solar PV systems are envisioned for the future.

The challenges that were delineated emphasised the importance of implementing strong security protocols, taking scalability into account, and adopting a comprehensive approach to ensuring the dependability of the system. In anticipation of the future, objectives include the enhancement of ML algorithms to yield more precise predictions, the incorporation of edge computing to enable real-time responsiveness, and the verification of AI models' explainability. The potential integration of blockchain technology into interconnected systems could enhance their security. Throughout this paradigm shift, the integration of cutting-edge technologies propels us towards an energy frontier that is both environmentally sustainable and highly efficient.

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