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Review

Artificial Intelligence of Things for Solar Energy Monitoring and Control

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Abstract: In the rapidly evolving field of renewable energy, integrating Artificial Intelligence (AI) and the Internet of Things (IoT) has become a transformative strategy for improving solar energy monitoring and control. This paper provides a comprehensive survey of Artificial Intelligence of Things (AIoT) applications in solar energy, illustrating how IoT technologies enable real-time monitoring, system optimization through techniques such as Maximum Power Point Tracking (MPPT), solar tracking, and automated cleaning. Simultaneously, AI boosts these capabilities through energy forecasting, optimization, predictive maintenance, and fault detection, significantly enhancing system performance and reliability. This review highlights key advancements, challenges, and practical applications of AIoT in the solar energy sector, emphasizing its role in advancing energy efficiency and sustainability.

Keywords: artificial intelligence; internet of things; artificial intelligence of things; photovoltaic; fault detection and diagnosis; predictive maintenance; energy forecasting; solar energy monitoring; solar tracking; automated cleaning systems

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1. Introduction

Approximately 75% of the world's fossil fuel consumption is used to generate heat and electricity, which has significant consequences for the environment and public health [1]. The combustion of fossil fuels such as coal, natural gas, and petroleum releases toxic pollutants that contribute to land and air pollution, global warming, and various health risks [2]. Additionally, fossil fuels are finite. Some projections estimate that, if current consumption trends continue, oil and gas reserves could decline to 14% and 18%, respectively, by 2050 [3]. These concerns emphasize the urgent need to transition to renewable and sustainable energy sources to reduce environmental harm and conserve resources for future generations. Governments worldwide are increasingly adopting clean energy policies, with solar energy gaining particular attention due to its wide availability. The Earth receives an average solar radiation of 343 W/m^2. In China, which is the leading emitter of carbon dioxide, solar photovoltaic (PV) technology has the potential to generate 131.942 petawatt-hours (PWh) of energy—an amount estimated to be nearly 23 times the country's total electricity demand [4]. In 2024, global solar PV capacity grew by a record 553 gigawatts (GW), increasing the total installed capacity to approximately 1200 GW [5]. Major installations in China, the United States, and India were key drivers of this growth. As a result, solar energy generation exceeded 2000 terawatt-hours (TWh) globally, contributing around 6.9% of the world's electricity supply [6]. This rapid expansion underscores the central role of solar energy in the transition toward cleaner power systems. To fully capitalize on this resource, effective

monitoring and control systems are essential. These systems ensure optimal management of energy production and meet rising electricity demands. Solar energy monitoring relies on components such as sensors and microcontrollers that support real-time tracking and performance optimization [7]. Alongside monitoring, control systems are critical for adjusting panel operations dynamically based on real-time data, improving efficiency and responsiveness. Fault detection also plays a vital role in maintaining system performance and extending operational lifespan. Recent advancements have introduced intelligent and automated methods for identifying faults in PV systems. By using IoT-enabled monitoring devices, these technologies support real-time detection of issues, enhancing the overall reliability and effectiveness of solar energy systems [8]. Building upon IoT capabilities, AI introduces advanced data analytics to improve energy forecasting, optimize panel orientation, and reduce operational costs. AI algorithms analyze both real-time and historical data to anticipate weather patterns, detect faults, and schedule maintenance proactively. These capabilities help avoid system failures and improve the longevity of PV installations. Moreover, AI contributes to smart grid integration by accurately predicting energy demand, further improving the stability and scalability of solar power networks [9–13]. Together, AI and IoT—known as AIoT—represent a unified approach that combines intelligent data processing with connected devices to maximize the performance of solar energy systems.

This survey examines the integration of AIoT in solar energy systems, focusing on IoT-enabled technologies for real-time monitoring, energy optimization through tracking and cleaning systems, and AI-driven applications for fault detection, predictive maintenance, and energy forecasting.

1.1. Existing Reviews and Our Contributions

Previous surveys have examined the role of AI and IoT in solar energy monitoring and control, but most studies focus on these technologies in isolation rather than exploring their combined potential. While some reviews address AI-driven energy forecasting and optimization techniques, others concentrate on IoT-enabled monitoring and automation systems. However, significant gaps remain in the literature, including the absence of a unified framework for AIoT in solar energy systems, limited analysis of how AI and IoT collaboratively optimize performance, and a lack of comprehensive taxonomies categorizing their applications. To fill these gaps, this survey offers a structured taxonomy and a detailed analysis of AIoT applications in solar energy. We classify AIoT implementations into key areas such as fault detection, predictive maintenance, energy forecasting, solar monitoring systems, and optimization techniques like MPPT, solar tracking, and automated cleaning. Furthermore, we compare existing studies to highlight differences in methodologies, findings, and technological approaches, providing a broader perspective on AIoT's role in solar energy. By consolidating advancements, identifying challenges, and analyzing key differences across studies, this paper aims to offer valuable insights that can inform future research and development in AIoT-driven solar energy solutions.

Table 1 summarizes the strengths and weaknesses of existing reviews and highlights the research gaps that our survey addresses.

Table 1. Summary of strengths, weaknesses, and gaps in existing reviews.

Element	Observation
Strengths of Existing Reviews	• Provide focused insights on either AI or IoT applications in solar energy. • Cover specific topics such as energy forecasting, MPPT algorithms, and IoT-based monitoring systems. • Offer foundational understanding of individual technologies.
Weaknesses of Existing Reviews	• Lack of integrated perspective on AIoT (AI + IoT synergy). • Limited discussion on real-time systems such as automated cleaning, tracking, and scheduling. • Absence of comprehensive taxonomies for categorizing AIoT applications. • Few reviews cover implementation challenges.
Gaps Identified and Addressed in This Survey	• Emphasis on integrated AIoT solutions tailored to solar energy systems. • Introduction of a unified framework and structured taxonomy. • Comprehensive classification of AIoT applications across key domains. • Comparative analysis of existing studies, highlighting methodological trends.

1.2. Survey Methodology

To ensure a comprehensive and systematic review, we employed a structured methodology to select, analyze, and compare relevant studies on AIoT in solar energy.

Search Process: We conducted a systematic search using Google Scholar to identify relevant articles, the majority of the results sourced from IEEE, as well as journals published by MDPI and Elsevier. The search focused on peer-reviewed journal articles, conference papers, and review studies related to AI, IoT, and their integration in solar energy management. Keywords included "AIoT in solar energy", "IoT-based solar monitoring", "AI in photovoltaic systems", and "fault detection in PV systems".

Inclusion Criteria: Our selection criteria ensured that we included studies specifically addressing AIoT applications in solar energy monitoring, optimization, fault detection, and predictive maintenance. In addition, we incorporated papers that provided fundamental definitions of AI and IoT to establish a strong theoretical foundation for our survey. Although we primarily focused on recent research, we also included some older articles that remain highly cited and influential in shaping AI and IoT applications in solar energy. These older studies were necessary for understanding the historical evolution of AIoT technologies and their impact on current advancements.

Exclusion: we excluded general AI or IoT research without a clear focus on solar energy, non-peer-reviewed articles, and outdated studies with limited relevance to modern AIoT applications.

Bibliometric Analysis: Our survey is based on a thorough review of 199 research papers, of which 127 specifically focus on the application of AI and IoT in PV systems. The distribution of these 127 papers over the years is shown in Figure 1. The remaining studies cover various aspects, including foundational definitions. The primary focus was on studies published between 2015 and 2025, ensuring that we captured the most recent advancements and emerging trends in the field.

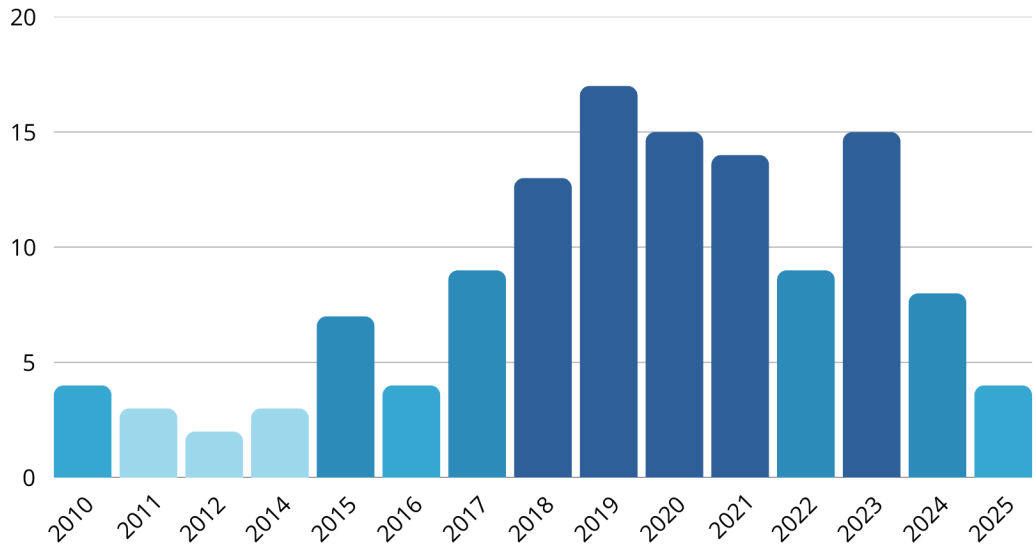


Figure 1. Distribution of surveyed papers on AI and IoT applications in PV systems over the years.

1.3. Survey Organization

To ensure a structured and comprehensive review, this paper is organized as follows: Section 2 provides an overview of AI and IoT, explaining their fundamental concepts and roles in solar energy applications. It also highlights key enabling technologies for AIoT, including machine learning algorithms, deep learning models, IoT sensors, communication protocols, and cloud computing. Section 3 categorizes and discusses AIoT applications in solar energy, including monitoring systems, fault detection and diagnosis in PV systems, predictive maintenance, energy forecasting, and optimization techniques such as MPPT, solar tracking, and automated cleaning systems to enhance energy efficiency. Section 4 discusses the key challenges in AIoT-based solar energy systems and offers insights for future optimization of their functionality. Section 5 concludes with a summary of the key findings of this survey. Figure 2 provides a structured overview of the survey, outlining its key sections and the main topics covered.

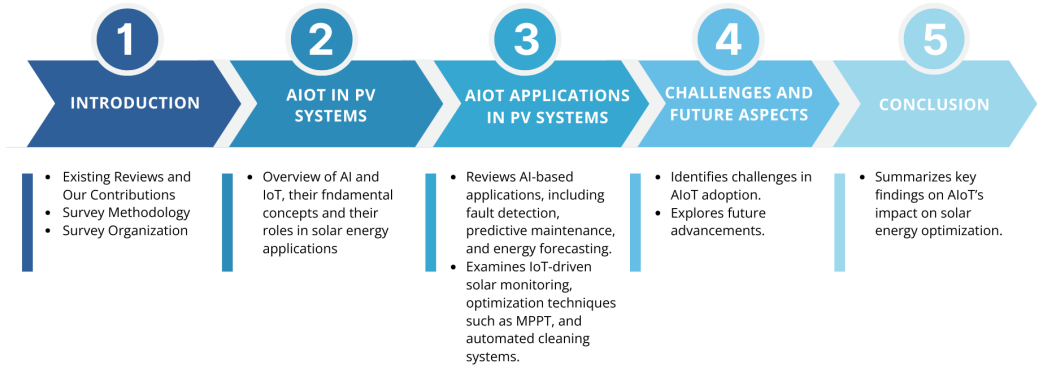


Figure 2. Survey roadmap: key topics and structure.

2. AIoT in PV Systems: Background

The integration of AIoT in PV systems is revolutionizing the monitoring, control, and optimization of solar energy. This section offers an overview of the key components of AIoT, including AI techniques that enhance PV system performance and the role of IoT in enabling seamless connectivity and data collection.

2.1. Artificial Intelligence Techniques

Artificial Intelligence (AI) refers to the development of systems capable of performing tasks that typically require human intelligence, such as reasoning, learning, problem-solving, and language understanding [14]. AI encompasses a broad range of techniques and methodologies designed to enable machines to replicate or enhance human capabilities.

According to the literature, machine learning (ML) is especially effective for addressing complex problems where traditional techniques either fail or are difficult to apply. ML excels in dynamic environments, as it can easily adapt to new data. Unlike traditional methods, ML is particularly advantageous in situations where there is no clear or direct relationship between inputs and outputs, making it ideal for problems that involve long and complex rules.

Deep learning (DL) builds on machine learning by providing enhanced accuracy in classification and prediction tasks, particularly when trained on large datasets. DL algorithms can process raw data directly and automatically extract relevant features, eliminating the need for manual feature engineering. This makes DL especially suitable for solving complex problems that go beyond the capabilities of traditional ML approaches. However, when data are limited, ML algorithms often outperform DL methods due to their lower data requirements.

Recently, Generative AI (GenAI), a cutting-edge field within AI, has garnered significant attention. Unlike traditional AI models, which perform deterministic tasks based on predefined rules, GenAI models learn patterns and structures from large datasets to generate text, images, audio, and even synthetic data that are virtually indistinguishable from real data [15].

Importantly, there are no universal rules for selecting the most suitable AI technique for a given application [16]. The choice depends on several factors: the nature of the problem, the volume of available data, the complexity of the algorithm, the implementation difficulty, and the desired accuracy and generalization capability.

This variability underscores the importance of understanding both the problem and the available tools when selecting the most appropriate technique

The Venn diagram in Figure 3 illustrates the relationships and overlaps among AI, ML, DL, and GenAI, highlighting both their unique features and shared capabilities. This representation emphasizes the hierarchical structure and interrelated nature of these technologies.

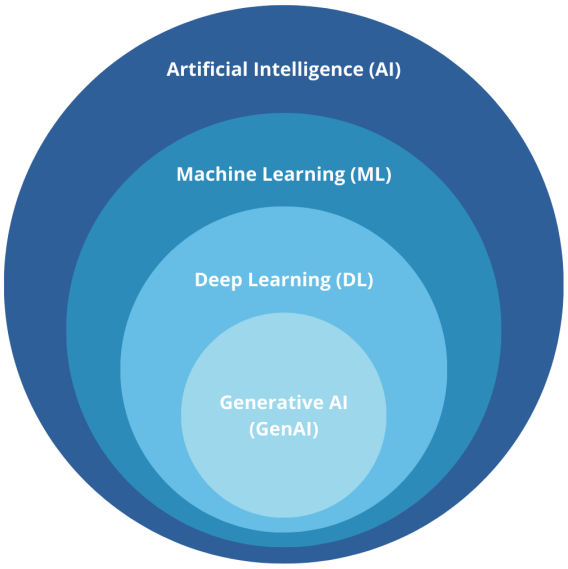


Figure 3. Venn diagram representing AI, ML, DL, and GenAI.

2.1.1. Machine Learning

Machine learning (ML) is a subset of Artificial Intelligence that enables systems to learn from data and improve their performance over time without being explicitly programmed. It focuses on developing algorithms that can identify patterns and make decisions with minimal human intervention [17].

ML is broadly categorized into the following paradigms, each suited to specific types of problems:

- **Supervised Learning:** Models are trained on labeled datasets, where each input has a corresponding output. This approach is ideal for both regression and classification tasks [14]. In solar panel monitoring, it can be used to classify panel conditions (e.g., normal, dusty, or damaged) based on labeled historical data.
- **Semi-Supervised Learning:** This hybrid approach leverages a small amount of labeled data alongside a large volume of unlabeled data. The model learns correlations between labeled and unlabeled instances, then uses the labeled data to guide the labeling of the remaining dataset [18]. This is particularly useful in PV system analysis, where labeled fault data may be limited, but abundant sensor or image data are available.
- **Unsupervised Learning:** This approach works with unlabeled data to discover hidden patterns or groupings, using techniques such as clustering and dimensionality reduction [19]. It is suitable for anomaly detection or grouping similar fault types in PV systems without requiring labeled data.
- **Reinforcement Learning:** Models learn by interacting with an environment and receiving feedback through rewards or penalties [20]. This method can be applied to optimize cleaning schedules for solar panels or manage adaptive control of energy flow in solar farms.

Figure 4 outlines the key ML algorithms commonly associated with each learning paradigm.

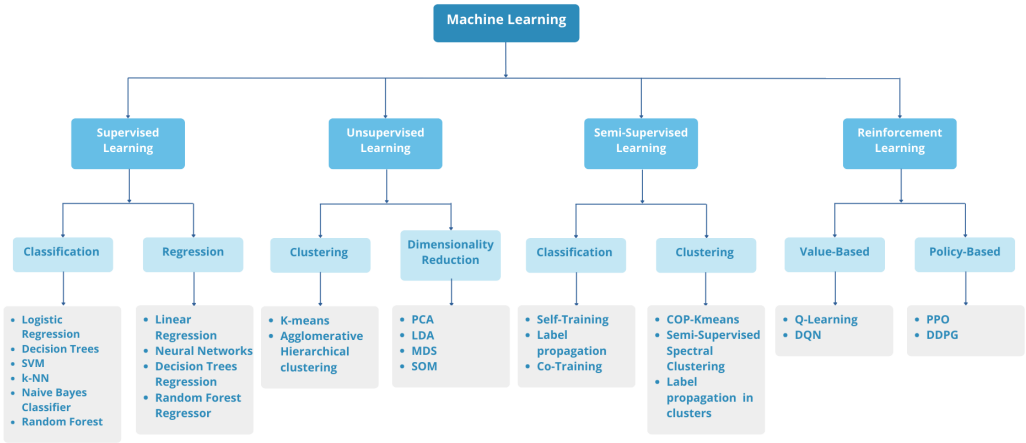


Figure 4. Categorization of ML algorithms by paradigm.

A typical machine learning workflow is illustrated in Figure 5. It begins with data collection and preprocessing to ensure data quality and consistency. The process continues with identifying the problem type classification or regression, which determines the selection of an appropriate algorithm. The dataset is split into training and test sets. Model selection is carried out using cross-validation and hyperparameter tuning. This procedure can be repeated for different machine learning algorithms, allowing performance metrics to be compared. The model with the highest evaluation score is then selected as the final candidate.

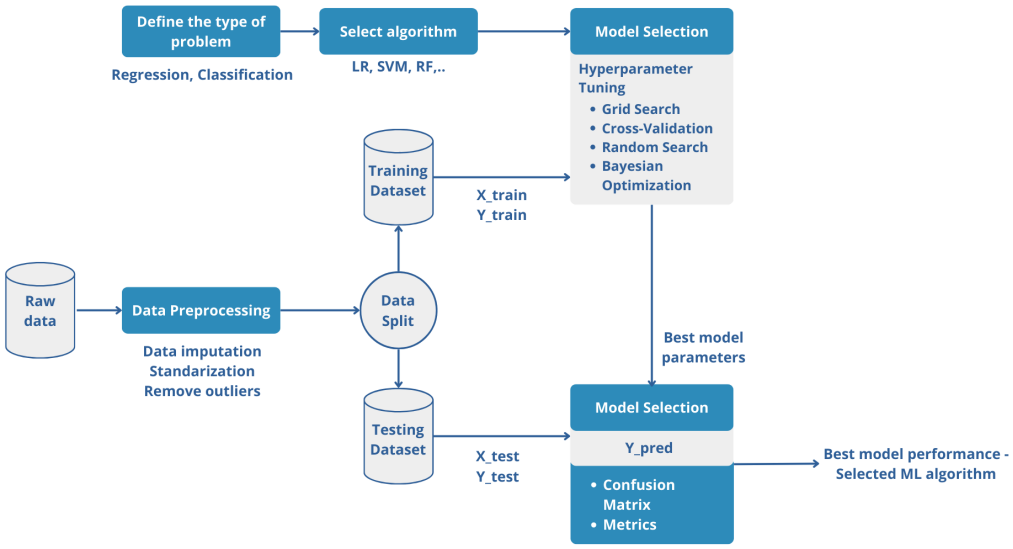


Figure 5. Workflow for the development of a machine learning model.

2.1.2. Deep Learning

Deep learning (DL) is a specialized subset of machine learning, inspired by the structure and function of the human brain. It utilizes Artificial Neural Networks—particularly Deep Neural Networks—to process and learn from large volumes of data [21].

DL relies on neural networks composed of interconnected layers. These include the input layer, which receives raw data; one or more hidden layers, where computations are performed through nodes (neurons) using activation functions; and the output layer, which produces the final prediction or classification [22] (see Figure 6). This layered architecture enables DL models to process complex data and extract meaningful patterns effectively.

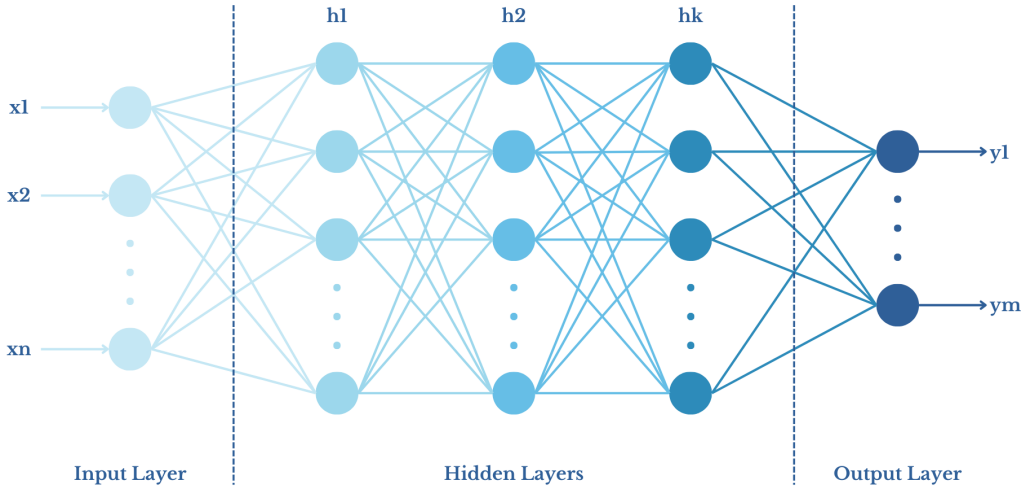


Figure 6. DL neural network architecture.

A fundamental mechanism that enables deep learning is backpropagation, an optimization technique used to minimize prediction errors by adjusting the weights of a neural network. It operates by propagating the error backward from the output layer to the earlier layers, allowing the model to iteratively update its parameters and refine its predictions. Backpropagation is essential for efficiently training deep networks, enabling them to learn complex patterns, improve performance, and generalize effectively across diverse datasets (see Figure 7).

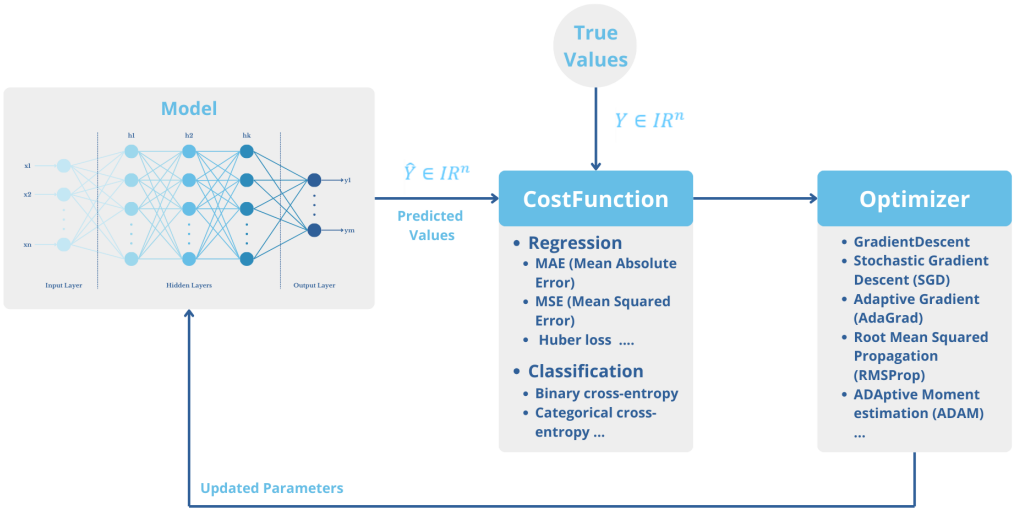


Figure 7. Backpropagation workflow in deep learning.

There are several types of architectures in DL, each suited for different tasks.

- **Convolutional Neural Networks (CNNs)**: These are particularly effective for image and video processing, utilizing convolutional layers to detect spatial hierarchies and patterns in data [21]. In the context of solar panel monitoring, CNNs can analyze UAV or satellite imagery to detect faults such as cracks, hot spots, or dust accumulation.
- **Recurrent Neural Networks (RNNs)**: Designed for sequential data, RNNs are well suited to tasks involving time series or natural language processing, where temporal dependencies are critical. In solar energy systems, RNNs can be employed to forecast energy production by analyzing historical weather and energy data, thereby aiding in performance optimization.
- **Long short-term memory (LSTM)**: A specialized form of RNN, LSTMs are engineered to capture long-term dependencies and retain information over extended time intervals [23]. They are particularly useful in predictive maintenance by identifying temporal patterns in time series sensor data that may signal potential equipment failures.

Training deep learning models typically requires large amounts of labeled data. During the learning phase, these models utilize optimization techniques such as gradient descent and backpropagation to adjust network weights and minimize prediction errors. Gradient descent iteratively updates model parameters by moving in the direction that reduces the cost function, thereby finding the optimal solution. Backpropagation complements this process by computing the gradient of the cost function with respect to each weight using the chain rule, allowing the error to be propagated backward from the output layer to the input layer [24].

Deep learning models thrive on large datasets, often requiring thousands or even millions of samples to achieve optimal performance. The increasing availability of vast datasets and computational power has been a key driver of recent advancements in DL, enabling the development of highly accurate models that frequently outperform traditional machine learning approaches across a wide range of applications [25].

2.1.3. Generative AI

Generative AI (GenAI) represents a transformative branch of Artificial Intelligence focused on generating new content by learning patterns from existing data. It employs advanced machine learning techniques, particularly deep learning models [26], which are trained on large volumes of unstructured data. This enables the models to learn the underlying structures and relationships within the data. As a result, GenAI has led to signif-

icant breakthroughs across various domains, including natural language processing, image synthesis, and autonomous decision-making. In the context of PV system monitoring and control, GenAI can enhance fault detection, predictive maintenance, and energy forecasting by generating realistic simulations, detecting anomalies, and automating control strategies.

Core components of GenAI include the following:

- **Generative Adversarial Networks (GANs):** GANs consist of two neural networks—the generator and the discriminator—that are trained simultaneously in a competitive process. The generator creates synthetic data, while the discriminator assesses its authenticity. Through this adversarial training process, the generator gradually improves its ability to produce realistic data [27] (see Figure 8). GANs can be particularly useful for generating synthetic sensor data in cases where real-world datasets are limited or incomplete. This capability is especially valuable for PV fault detection and anomaly prediction, as GANs can simulate a range of fault scenarios (e.g., shading, panel degradation), enhancing the robustness of AI models.
- **Variational Autoencoders (VAEs):** VAEs are another powerful technique within Generative AI. They work by encoding input data into a latent space, which is then decoded back into the original data space. This encoding–decoding process enables VAEs to generate new data points by sampling from the latent space, making them highly suitable for applications such as image generation and data augmentation [28]. In the context of PV systems, VAEs can be employed for anomaly detection by learning the normal operational behavior of solar panels and identifying deviations that may signal potential faults. This capability supports real-time monitoring and proactive maintenance by detecting early signs of performance degradation or energy losses.
- **Transformers:** Transformers are a type of architecture used for natural language generation and understanding. Models like GPT (Generative Pre-trained Transformer) and BERT are based on the Transformer architecture. These models use self-attention mechanisms to capture dependencies and relationships within text, making them the backbone of large language models (LLMs) [29]. The Transformer architecture follows a structured workflow, as illustrated in Figure 9, where input text is first tokenized and converted into dense vector representations through an embedding layer, followed by positional encoding to incorporate order information. The encoder layers then apply multi-head self-attention mechanisms to capture relationships between tokens while processing information in parallel. The decoder layers generate output step by step using masked self-attention and cross-attention with encoder outputs, ultimately producing a probability distribution over the vocabulary through a final softmax layer to generate meaningful responses. Transformer-based models, such as LLMs, can enhance PV system monitoring through automated analysis of maintenance logs, fault reports, and operational data. By processing large volumes of text data, LLMs can assist engineers in diagnosing faults, summarizing reports, and even predicting optimal maintenance schedules.
- **Diffusion Models:** Recently popularized for generating high-quality images, diffusion models operate by progressively refining random noise into detailed outputs. These models iteratively enhance image quality, making them highly effective for tasks that require generating realistic images from scratch [30]. In the context of photovoltaic (PV) system performance optimization, diffusion models can simulate environmental conditions, such as cloud cover and temperature fluctuations, to predict their impact on energy generation. Additionally, these models can generate high-resolution simulations of weather patterns, which can support energy forecasting and grid integration planning.

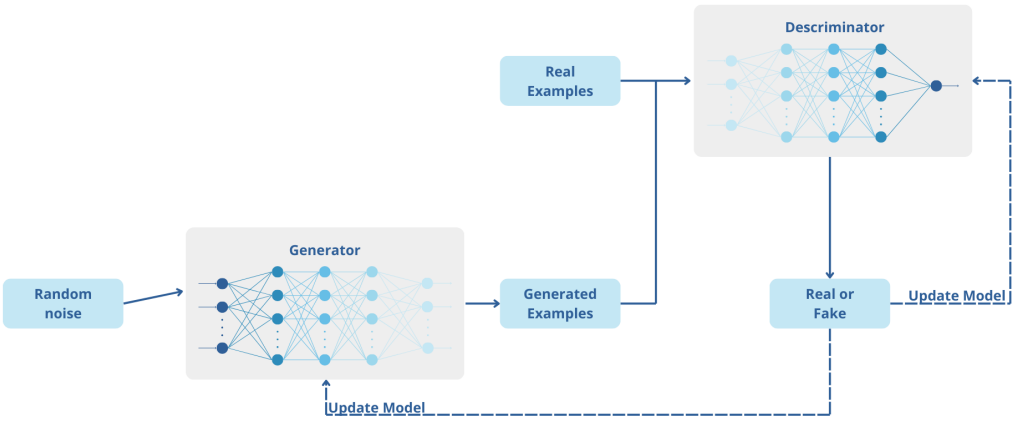


Figure 8. GAN architecture.

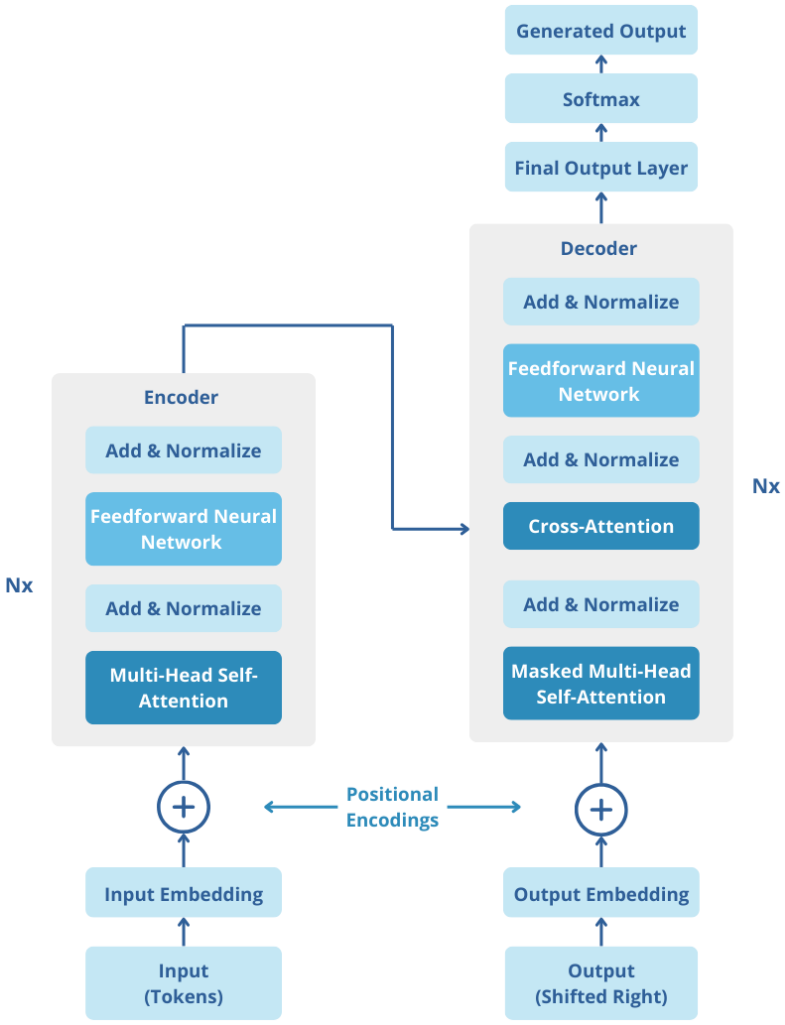


Figure 9. Transformer architecture.

Generative AI has the potential to revolutionize photovoltaic (PV) system monitoring by enhancing predictive capabilities, optimizing energy management strategies, and reducing operational risks. However, challenges such as high computational demands, data bias, and issues with interpretability must be addressed to ensure the reliable, ethical, and effective deployment of GenAI-driven solutions in solar energy management.

2.2. Internet of Things

The advent of the internet has been a significant boon to humanity, unlocking countless applications and enabling seamless communication between devices. This emerging technology, known as the Internet of Things (IoT), leverages the internet to facilitate connectivity between physical devices, or "things" [31].

By utilizing sensors and communication networks, these devices can collect valuable data and offer a wide range of services. These include applications such as remote monitoring and control, predictive maintenance, energy optimization, and other functionalities designed to maximize solar energy generation, enhance system reliability, and ensure efficient energy management.

When designing IoT systems, the first step is to define the application, which refers to the use case or the problem the system will address. This is followed by selecting the appropriate components, such as sensor devices, communication protocols, data storage, and computational infrastructure. An IoT platform requires the integration of environmental sensors and suitable communication technologies to effectively achieve its objectives [32]. The components of an IoT platform are illustrated in Figure 10.

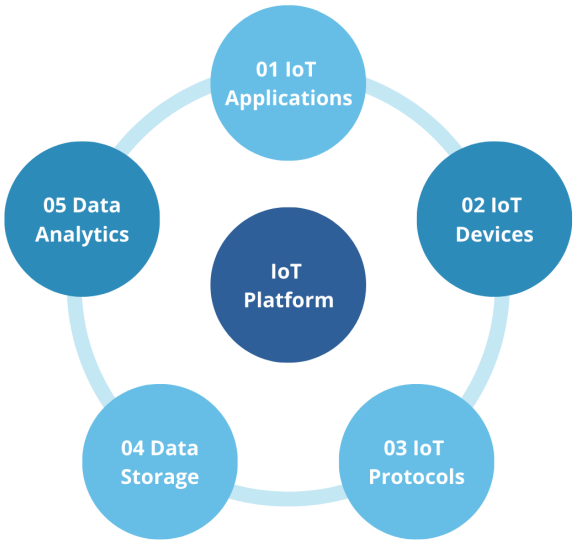


Figure 10. Diagram describing the components of an IoT platform.

Core Technologies Enabling IoT Systems

Technologies enabling IoT systems are revolutionizing the management of photovoltaic (PV) systems by enhancing efficiency, reliability, and performance. IoT integrates advanced sensors, actuators, communication technologies, and computing methods to monitor parameters such as solar irradiance, panel temperature, and energy output in real time. These capabilities support remote monitoring, predictive maintenance, and rapid fault detection, significantly reducing operational costs and downtime. The ongoing evolution of IoT highlights its crucial role in advancing renewable energy solutions and ensuring optimal energy generation. This section delves into the core technologies that enable IoT in PV systems.

Sensors are crucial components in IoT systems, enabling real-time data collection and improving system efficiency [33]. In photovoltaic (PV) systems, sensors monitor key parameters such as solar irradiance and temperature, helping optimize performance and facilitating smart energy management for both cost and energy savings [34]. One such sensor is the temperature sensor, which plays a vital role in monitoring the temperature of PV panels and inverters. These sensors help detect overheating issues and optimize cooling

mechanisms, ensuring consistent energy output. High temperatures, if not managed properly, can significantly reduce panel efficiency [33,35].

Additionally, humidity sensors are valuable in assessing environmental conditions that may impact panel performance, such as moisture accumulation, which can lead to degradation or electrical leakage [36]. Light sensors, on the other hand, are essential for tracking solar irradiance and sunlight intensity. These data help optimize panel alignment in solar tracking systems, ensuring maximum energy generation by adjusting the panels to varying light conditions [37,38].

Current and voltage sensors are integral to PV systems, as they monitor the electrical output of the panels and inverters, helping detect inefficiencies or faults in energy production. Additionally, dust and soiling sensors track the accumulation of dust and debris on PV panels, which can significantly reduce energy efficiency. By providing these data, these sensors enable the scheduling of timely cleaning to maintain optimal panel performance [39]. Furthermore, pyranometers are used to measure global solar radiation, providing essential data for evaluating system performance relative to expected energy generation.

Once the sensors collect and analyze data, the system activates actuators to perform the necessary mechanical actions, ensuring optimal operation. In PV systems, actuators play a crucial role in optimizing performance by adjusting the angles of solar panels in tracking systems, automating cleaning mechanisms, and enabling remote control of switches and inverters. This integration enhances automation, efficiency, and overall energy management [40]. Pneumatic actuators use compressed air to generate motion and are occasionally employed in PV systems, particularly in cleaning systems, where they provide quick and precise movement for panel maintenance and debris removal. In contrast, electric actuators rely on external energy sources, such as batteries, to produce linear or rotary motion. These are widely used in PV systems to adjust the tilt and orientation of solar panels in solar tracking systems, ensuring panels follow the sun's path to maximize energy capture. Electric actuators are also integral to automated cleaning systems, helping maintain panel efficiency by removing dust and debris.

Wireless communication technologies are integral to the functionality of IoT systems, enabling seamless data transfer between sensor devices, IoT gateways, and other system components. These technologies vary based on factors such as communication range, bandwidth, and power efficiency. In PV systems, ensuring reliable communication is particularly important, especially in remote locations where solar plants are often situated. Therefore, selecting technologies that support continuous, real-time, and energy-efficient data transfer is crucial for monitoring performance, managing energy generation, and enabling remote maintenance [41]. Short-range technologies are well suited for localized monitoring and control, ensuring the efficient operation and integration of PV components within smart energy networks. Wi-Fi, for instance, is commonly used for monitoring energy production and system performance, allowing remote access and control. However, its high power consumption makes it less ideal for energy-sensitive applications like PV systems, where energy efficiency is paramount [41,42]. Bluetooth Low Energy (BLE) is a cost-effective communication technology with a range of up to 30 m, making it ideal for small-scale IoT applications in PV systems. BLE is particularly useful in energy management systems for monitoring and controlling PV systems in smart homes and offices, enabling optimized energy consumption through enhanced communication between devices [43,44]. Zigbee, designed for low-power applications with a communication range of up to 100 m (extendable through mesh networks), is widely used in PV systems. It supports smart grid integration, energy monitoring, and home automation, optimizing energy usage by enabling seamless communication between PV components such as inverters, sensors, and controllers [45,46]. Low-Power Wide Area Network (LPWAN) technologies are crucial

for enabling long-range, energy-efficient communication in IoT systems. These technologies are particularly valuable for remote monitoring and management of PV systems, especially in large-scale or isolated installations. LoRa, a widely adopted LPWAN technology, offers long-range communication (over 10 km in rural areas) with low power consumption, making it ideal for smart grids and building automation. In PV systems, LoRa is used for energy management and monitoring over large distances, particularly in remote areas [47,48]. Satellite technologies play a crucial role in PV systems, especially in remote or off-grid areas where traditional communication networks are unavailable. These technologies enable seamless data transmission between PV systems and central monitoring centers, ensuring continuous performance tracking, fault detection, and maintenance planning. For large-scale solar farms or isolated installations, satellite communication provides a reliable means to monitor parameters such as energy generation, weather conditions, and system efficiency. This ensures that operators can remotely manage and optimize PV systems, reducing the need for on-site intervention and lowering operational costs [49,50]. Table 2 presents a comparison of wireless communication technologies in PV systems.

Table 2. Comparison of wireless communication technologies in PV systems.

Technology	Range	Power Consumption	Applications in PV Systems
Wi-Fi	≤100 m	High	Monitoring and remote control of energy production and system performance. Less suitable for PV systems.
Bluetooth Low Energy (BLE)	≤30 m	Low	Small-scale PV systems in smart homes and offices.
Zigbee	≤100 m	Very Low	Smart grid integration, energy monitoring, and enabling efficient communication between PV components.
LoRa (LPWAN)	≤50 km	Very Low	Monitoring and energy management in large-scale and remote PV installations.
Satellite Communication	≥1500 km	High	Remote or off-grid PV systems, enabling performance tracking, fault detection, and system optimization in large-scale solar farms.

Wired communication protocols ensure reliable, low-latency data transfer and seamless integration in IoT systems, particularly in industrial and energy applications. PROFINET is an industrial Ethernet protocol for fast and secure data communication in automation systems [51]. In PV systems, PROFINET plays a key role in connecting components like PLCs (Programmable Logic Controllers), inverters, and sensors to allow real-time monitoring and control. It helps transfer essential data such as voltage, current, and temperature from the field to the control center, making the system more efficient. PROFINET can also link PV systems with SCADA software platforms for centralized supervision, fault detection, and performance analysis. Its high-speed and reliable communication makes it especially useful for large-scale solar setups and smart grid integration. On the other hand, Modbus protocol is essential for enabling communication between devices in automation systems, allowing data to be exchanged through regular polling. It supports interdependent control variables across different hardware, ensuring coordinated updates [52]. Modbus has a long-standing presence in industrial automation, and its TCP version is widely adopted in advanced industrial contexts such as Industry 4.0 and the Industrial Internet of Things (IIoT) [53]. In PV systems, Modbus can monitor and control various components like inverters, batteries, and environmental sensors, ensuring real-time data acquisition and effective system management. Together, Modbus and PROFINET can complement each other, with PROFINET handling high-speed communication and Mod-

bus managing data exchange across various devices, creating an integrated and efficient system. Another well-known protocol is RS-485, also referred to as EIA-485. This protocol supports networks with up to 32 nodes. It operates on a master–slave communication model, where packets exchange data. The transmission speed can reach up to 10 Mbps over short distances (around 12 m) and up to 100 kbps for longer distances, with a maximum range of approximately 1333 m [54]. In PV systems, RS-485 is commonly used for wired communication between inverters, energy meters, and monitoring devices. Its long-distance capability and noise resistance make it ideal for transmitting data such as voltage, current, power output, and fault signals from solar inverters to a central controller or data logger. This enables real-time performance tracking, fault detection, and integration with SCADA systems in both residential and large-scale solar installations. MQTT, or Message Queuing Telemetry Transport, is a lightweight, efficient protocol widely used in IoT for communication between resource-constrained devices due to its low power consumption, scalability, and reliable message delivery. However, it faces security concerns, leading to research on vulnerabilities and defense mechanisms [55]. In PV systems, MQTT enables real-time monitoring and efficient data transfer between solar panels, inverters, batteries, and monitoring systems, helping track performance metrics like voltage and current, while facilitating remote monitoring and analysis.

IoT data analysis is important for optimizing PV systems, improving energy efficiency, and enabling timely decision-making. PV systems generate large volumes of data, which present challenges due to their high volume, speed, and variety. Traditional methods struggle with these "Big Data", necessitating advanced computing techniques like edge computing, cloud computing, or fog computing to process and extract insights. These methods enable real-time decision-making, predictive maintenance, and optimization of energy output, especially for large-scale or remote PV installations [56–58]. Starting with the edge computing paradigm, widely applied, it involves processing data closer to the source of generation, which in this case is the solar panel. In PV systems, edge computing enables real-time monitoring of energy production, system performance, and environmental conditions by analyzing data locally, without relying heavily on distant cloud servers. This results in reduced latency, quicker response times for control systems, and enhanced efficiency in energy management. By decentralizing computation, edge computing improves scalability and reliability in remote PV installations, ensuring continuous operation even in areas with unreliable internet access [59]. Additionally, it strengthens security and privacy by limiting the transmission of sensitive data to the cloud, reducing vulnerability to cyber threats [60]. Cloud computing refers to delivering computing services, applications, storage, and processing over the internet. It relies on centralized hardware systems located in data centers to handle vast amounts of IoT data, providing robust computational capabilities [61,62]. It is cost-reduced since it eliminates the need for expensive hardware and software [63]; also, it offers enhanced capacity by increasing computational power and storage through multi-core architectures [64], and it enables efficient analysis of large IoT datasets from any location [65]. Additionally, cloud computing minimizes the energy required for local data processing, offering an environmentally friendly solution. Its secure infrastructure further ensures reliable data storage and management [65]. In the context of PV systems, cloud computing is used to store and analyze vast amounts of data generated by IoT devices embedded in solar panels, inverters, and other system components. This enables remote monitoring, predictive maintenance, and optimization of energy generation, ensuring the efficient operation of PV systems. Cloud platforms provide the scalability needed to manage data from large-scale solar farms or multiple PV systems, while offering high-level data-processing capabilities that enhance the overall management and performance of solar energy operations. While fog computing extends cloud computing by

decentralizing data processing and moving it closer to the edge of the network, near IoT devices, this distributed paradigm addresses issues of latency and bandwidth limitations associated with centralized systems [66]. Devices such as personal computers, routers, and industrial controllers serve as fog nodes, processing data on site [67], offering faster response times and reduced network traffic compared to cloud computing [68], as well as ensuring secure processing and storage for applications requiring real-time decision-making [68]. Fog computing's ability to deliver faster, localized, and secure services makes it an efficient complement to cloud computing, especially for IoT applications that demand quick responses. In PV systems, fog computing is used to reduce the latency involved in data processing, allowing real-time analysis of energy generation and consumption data from solar panels and other PV components. By processing data closer to the source, such as at solar inverters or energy meters, fog computing minimizes the need to send large amounts of data to the cloud, improving both the speed and efficiency of monitoring and control processes. This localized computing also helps ensure that critical decisions, such as system adjustments and fault detection, can be made with minimal delay, enhancing the overall performance and reliability of PV systems. Table 3 presents a comparison of edge, cloud, and fog computing in PV Systems.

Table 3. Comparison of edge, cloud, and fog computing in PV systems.

Aspect	Edge Computing	Cloud Computing	Fog Computing
Data-Processing Location	Local, close to data source (solar panels)	Centralized, in remote data centers	Decentralized, close to edge devices (inverters)
Latency and Response Time	Very low latency, real-time processing	Higher latency due to distance to cloud servers	Lower latency than cloud, but not as fast as edge
Scalability	Limited scalability in remote areas	Highly scalable for large-scale PV systems	Scalable with local processing, complementing cloud
Security and Privacy	High security, minimal data transmission to cloud	Secure, but data transmission increases risk	Enhanced security by reducing data transmission to cloud
Energy Efficiency	Optimizes energy by processing locally	Minimizes local energy use but consumes more at data centers	More energy-efficient than cloud for localized processing
Use in PV Systems	Real-time monitoring of energy and performance	Stores and analyzes data from PV IoT devices	Reduces latency in monitoring and control, ensures faster decisions

3. AIoT Applications in PV Systems: A Comprehensive Review

With advancements in AI and the IoT, their applications in PV systems have become increasingly diverse and sophisticated. AI techniques enhance operational efficiency by detecting faults early, predicting maintenance needs, and improving energy forecasting. Meanwhile, IoT facilitates real-time data collection, remote monitoring, and automated control, ensuring optimal system performance.

This section explores AI-driven applications in PV systems, covering fault detection and diagnosis, predictive maintenance, and energy forecasting. Additionally, it examines IoT-based advancements, such as solar monitoring systems and optimization techniques like MPPT, solar tracking, and automated cleaning systems. These technologies collectively contribute to smarter, more efficient solar energy management.

3.1. Applications of AI in PV Systems

The integration of AI in PV systems has gained significant attention due to its potential to enhance efficiency, reliability, and predictability. This part explores the recent advancements and applications of AI techniques in PV systems, focusing on fault detection and diagnosis, predictive maintenance, and energy forecasting and optimization.

3.1.1. Fault Detection and Diagnosis

Fault detection and diagnosis are critical for maintaining the performance and reliability of PV systems. Timely detection and accurate classification of faults, such as short circuits, open circuits, and shading, are essential to minimize energy losses, prevent equipment damage, and reduce maintenance costs. Traditional fault detection methods often rely on manual inspections or simple threshold-based techniques, which may be insufficient for handling the complexity and variability of modern PV systems. Recent advancements in Artificial Intelligence have enabled the development of more sophisticated and efficient approaches for detecting and diagnosing a wide range of faults, even under dynamic and uncertain operating conditions.

Several studies have demonstrated the effectiveness of combining UAV imagery with AI algorithms for fault identification. For instance, Naveen et al. [69] developed an ensemble-based Deep Neural Network (DNN) model designed for the autonomous detection of visual faults in PV modules, such as glass breakage, burn marks, discoloration, and delamination. Utilizing an image dataset captured by an RGB camera mounted on an unmanned aerial vehicle (UAV), the process begins with image preprocessing, which involves extracting spatial and frequency domain features using methods like discrete Wavelet Transform (DWT), texture analysis, grey level co-occurrence matrix (GLCM), fast Fourier transform (FFT), and grey level difference method (GLDM). The processed images are then input into the DNN model for fault detection. Similarly, Prabhakaran et al. [70] applied a deep learning model with Region-Based Histogram Approach (RHA) preprocessing on RGB images, followed by the Grey Scale Quantization algorithm (GSQA) to refine image details, detecting panel defects such as spots, cracks, dust, and microcracks. The model was tested with different dataset sizes (500, 1000, and 2000 images), highlighting improved performance with larger datasets. Also, Singh et al. [71] employed a Support Vector Machine (SVM) with Histogram Equalization (HE) preprocessing to detect microcracks in PV cells based on the ELPV dataset. While highly accurate, the reliance on RGB images alone might miss thermal anomalies, such as hot spots, which are better captured by IR imaging.

Yin et al. [72] developed PV-YOLO, a modified YOLOX model, to detect and classify multiple faults in PV panels using drone-captured infrared (IR) images. This method demonstrates high accuracy in detecting multiple faults but may struggle under diverse environmental conditions that affect IR image quality.

Huang et al. [73] modified YOLOv5 to detect defects that pose electrical hazards in PV panels. While Ozer et al. [74] proposed a YOLOv5s model enhanced with Gaussian and Wavelet Transform preprocessing to detect panel conditions. In [75], researchers proposed a solution for automatically detecting and classifying the condition of PV panels using deep learning and UAV technology. The method combines YOLO-based deep learning models (YOLOv5, YOLOv7, and YOLOv8) with drone-captured images to classify panels as normal, dusty, or damaged. The system involves a dataset of 1100 RGB images processed with Histogram Equalization to enhance image quality before being fed into the model. Real-time testing with a Raspberry Pi 4B on a UAV demonstrated the method's effectiveness in accurately detecting and categorizing faults in solar panels.

UAV-based methods provide high-resolution imaging and scalability, making them invaluable for large-scale solar installations. However, they face challenges such as depen-

dency on environmental conditions, infrastructure requirements, and the need for robust preprocessing to enhance image quality. Additionally, their reliance on periodic inspections rather than continuous monitoring limits their effectiveness for real-time fault detection.

A detailed comparison of the UAV-based approaches is provided in Table 4, summarizing their methodologies, metrics, and limitations.

Table 4. Summary of UAV-based approaches on fault detection.

Study	Type of Faults	AI Technique	Key Metrics	Limitations
Naveen et al. [69]	Visual faults: - Glass breakage - Burn marks - Discoloration - Delamination	DNN with Random Forest classifier	Acc = 99.68%	Limited to RGB images captured by UAV, requires extensive preprocessing
Prabhakaran et al. [70]	- Spots - Cracks - Dust - Microcracks	DL with RHA and GSQA preprocessing	Acc = 87% (500 images), 93% (1000 images), 97% (2000 images)	Performance depends on dataset size; preprocessing is computationally expensive
Singh et al. [71]	- Microcracks	SVM with HE preprocessing	F1 Score: 94%	Limited to ELPV dataset, may not generalize to other datasets
Yin et al. [72]	- Multiple faults	PV-YOLO (Modified YOLOX)	Mean Average Precision (mAP): 92.56%	Focused on IR images, limiting applicability to RGB datasets
Huang et al. [73]	Defects posing electrical hazards	Modified YOLOv5	mAP: 95.5%, 1.5% increase in precision, 2.4% increase in recall	Improvements are incremental; model performance depends on dataset quality
Ozer et al. [74]	Panel conditions - Normal - Dusty - Damaged	YOLOv5s with Gaussian and Wavelet Transform preprocessing	F1 Score: 81% (without preprocessing), 87% (with preprocessing)	Preprocessing adds complexity; limited F1 score improvement
Ozer et al. [75]	- Normal - Dusty - Damaged	YOLOv5, YOLOv7, YOLOv8 with Histogram Equalization preprocessing	F1 Score: 97% (YOLOv5)	Limited real-time testing on Raspberry Pi 4B; requires UAV technology

While UAV-based methods excel in capturing high-resolution imagery, sensor-based approaches offer the advantage of real-time monitoring and fault detection. These techniques rely on electrical and environmental sensors to continuously monitor PV system performance.

Jiang and Maskell [76] combined Artificial Neural Networks (ANNs) with analytical models for automated fault detection and diagnosis in PV systems. Their method forecasts power output based on irradiance and temperature, comparing predicted and actual values to identify faults, offering a compact and high-accuracy solution by integrating parameters such as open-circuit voltage and short-circuit current for fault validation. Similarly, Abdallah et al. [77] proposed an intelligent solar panel monitoring system integrating ANNs and IoT platforms to detect shading and other PV faults. The ANN model estimates optimal power output using irradiance and temperature data, while discrepancies between predicted and actual output indicate performance issues. The IoT platform enables real-time visualization and fault alerting, enhancing energy efficiency and reducing maintenance costs. Benkercha and Moulahoum [78] utilized the C4.5 decision tree algorithm for fault

detection and diagnosis in grid-connected photovoltaic systems (GCPVS). Their approach processes ambient temperature, irradiation, and power ratio data to identify faults such as string faults, short circuits, and line–line faults. Over a five-day testing period, the model demonstrated high detection accuracy of 99.87% and diagnostic accuracy of 99.80%, proving its robustness for real-world applications. Similarly, Harrou et al. [79] introduced a k-nearest neighbors (kNN)-based fault detection technique, integrating Shewhart and exponentially weighted moving average (EWMA) monitoring schemes. The method uses residuals from simulation models combined with parametric and nonparametric thresholds for anomaly detection. Validated on a 9.54 kWp grid-connected PV system, the kNN-based approach achieved high accuracy and robustness against noise, outperforming traditional monitoring techniques and enhancing PV system reliability.

Dust accumulation is a common issue impacting PV efficiency. Hossain et al. [80] addressed the impact of dust on PV systems by developing an ML-based dust detection method and an automated cleaning system. The study implemented various ML classifiers, with the ANN model achieving the highest accuracy of 98.11%. Upon detecting dust, the system activates a water sprinkler to clean the panels, restoring efficiency to 14.87%. In a related effort, Mekki et al. [81] proposed an Artificial Neural Network-Based Model (ANNBM) to estimate power loss due to partial shading. The system uses a Multilayer Perceptron (MLP) to detect deviations between predicted and actual outputs, providing a computationally efficient alternative to complex mathematical models. Syafaruddin et al. [82] designed a three-layer ANN model targeting short-circuit fault localization in PV modules. While highly effective in identifying faulty modules, the system requires extensive data training for scalability across large PV installations. In the realm of arc fault detection, Lu et al. [83] introduced a novel DL-based methodology, DA-DCGAN (Domain Adaptation and Deep Convolutional Generative Adversarial Network). This technique generates synthetic arcing data from normal PV loop current data using a DCGAN and applies domain adaptation to train a lightweight CNN classifier for accurate cross-domain fault diagnosis. The approach was validated through real-time experiments on a 1.5 kW grid-connected PV system and pre-recorded data, achieving high detection accuracy. The DA-DCGAN eliminates reliance on real fault datasets, making it highly practical for real-world applications where labeled fault data are scarce.

Additional research has focused on improving fault classification accuracy. Chao et al. [84] developed a modified neural network model for fault diagnosis, integrating extension theory to improve learning efficiency and reduce memory consumption. The model achieved high accuracy in identifying 10 types of PV faults, outperforming traditional MLP networks. Similarly, Akram and Lotfifard [85] employed a Probabilistic Neural Network (PNN) for detecting, classifying, and locating faults in PV arrays. The method leverages environmental and electrical data to enhance fault detection accuracy. Based on manufacturer datasheet information, a novel PV system modeling technique was introduced to validate the approach. Building on the idea of Decision Tree algorithms, Zhao et al. [86] developed a Decision Tree (DT) model for fault detection and classification trained on 764,529 PV instances under 28 fault conditions, achieving high accuracy in both fault detection (up to 99.98%) and classification (up to 99.8%) and integrating into a microcontroller-based system for real-time monitoring. In parallel, Chen et al. [87] implemented a Random Forest (RF)-based fault detection model, analyzing array voltage and string currents without requiring environmental condition inputs such as irradiance or temperature to identify various PV faults, including line–line faults, degradation, open circuits, and partial shading. Their RF system, tested in MATLAB and real PV setups, achieved 99.994% detection accuracy and 99.952% classification accuracy but depended on large labeled datasets for training. Madeti and Singh [88] employed a kNN-based fault detection and classification technique,

focusing on real-time monitoring of faults like open circuit, line–line faults, and partial shading scenarios. The method, validated on experimental I-V characteristic data under varying irradiance and temperature conditions, achieved a high classification accuracy of 98.70%. Also, Zhao et al. [89] proposed a PV array fault diagnosis method combining Fuzzy C-Mean (FCM) clustering and fuzzy membership algorithms to improve accuracy and robustness in fault classification. The method clusters fault sample data into six fault types, such as short circuits and shading, using FCM and calculates membership degrees for fault diagnosis based on fuzzy normal distribution. The approach achieved 96% diagnostic accuracy in simulations and experiments, demonstrating scalability to new fault types and adaptability to transient conditions. This method is computationally efficient, independent of labeled datasets, and suitable for integration into SCADA (Supervisory Control and Data Acquisition) systems for real-time monitoring in complex environments. Lu et al. [90] introduced a fault diagnosis method leveraging CNNs and Electrical Time Series Graphs (ETSGs). Their approach converts sequential voltage and current data into 2D ETSGs, allowing the CNN architecture to automatically extract features. The model achieved over 99% accuracy in diagnosing open-circuit and line–line faults in experimental case studies. To address the challenges of manual feature extraction, Appiah et al. [91] presented a novel fault diagnosis technique using LSTM networks to automatically extract features from raw data for fault classification. The LSTM model outperformed traditional methods such as SVMs, ANNs, and PNNs, achieving high diagnostic accuracy even with noisy data, thereby eliminating the need for manual feature extraction. Similarly, Chen et al. [92] proposed a deep residual network (ResNet)-based fault detection and diagnosis model that addresses the limitations of manual feature extraction. By utilizing raw I-V curves, irradiance, and temperature data, the ResNet model demonstrated superior accuracy, reliability, and training efficiency compared to CNNs and other techniques, proving effective across simulated and real-world datasets.

Several studies focused on addressing uncertainties in PV systems. Cheng et al. [93] introduced a data fusion approach using fuzzy mathematics and evidence theory, which consolidates differences between measured and predicted values to improve fault localization in large-scale PV systems. Bonsignore et al. [94] employed a Neuro-Fuzzy approach for PV module parameter estimation under different conditions. Their AI-based diagnostic system accurately differentiates between normal and faulty operations, even in noisy environments. Additionally, Hempelmann et al. [95] evaluated unsupervised anomaly detection models for identifying rare faults in PV systems. Their study compared multiple models, with VAE achieving the highest detection rate of 92.06%, demonstrating the potential of unsupervised learning for real-time monitoring in environments with limited labeled data.

While much attention has been given to fault detection in PV modules and arrays, recent works have also explored fault diagnosis in the associated power conversion systems, which are crucial to ensure stable energy transfer and grid integration. In this regard, Kou et al. [96] proposed a novel fault diagnosis method combining feature transformation and Random Forests to identify open-circuit faults in IGBT switches within a three-phase PWM rectifier. Their approach leverages current trajectory slopes as features to enhance classification performance across varying load conditions, achieving high accuracy in localizing switch faults. Veerasamy et al. [97] developed an LSTM-based fault detection method for identifying High Impedance Faults (HIFs) using Wavelet-Transformed current features to enhance diagnostic accuracy in solar-integrated grids. Validated on a PV-integrated IEEE 13-bus system, the model achieved over 91% accuracy, outperforming other classifiers and confirming the efficacy of deep learning in grid fault classification. In addition, Li et al. [98] introduced a hybrid-driven approach based on model data to detect open switch faults in converters. By fusing model-based analysis with ANN learning, their

method offers near-instantaneous fault diagnosis under dynamic conditions, achieving high robustness and low computational burden.

Although sensor-based approaches offer significant advantages, challenges such as computational efficiency, data requirements, and scalability remain areas for future research. Integrating lightweight AI models and hybrid techniques could further enhance the effectiveness of sensor-based fault detection in large-scale PV systems.

Table 5 provides a comparative analysis of these studies, summarizing their techniques, metrics, strengths, and limitations.

Table 5. Summary of sensor-based approaches on fault detection.

Study	Approach	AI Technique	Input Data	Fault Type Detected	Key Metrics	Limitations
Jiang and Maskell [76]	Fault detection and diagnosis	ANN + Analytical Methods	Irradiance, Temperature, Open-circuit voltage, Short-circuit current	Open/Short-circuit Faults, Non-uniform conditions, Inverter faults, MPPT faults	High accuracy, rapid fault detection	Computationally Intensive
Abdallah et al. [77]	Fault detection	ANN + IoT	Irradiance, Temperature	Shading and other faults	Real-time alerts, high accuracy	Requires continuous data connectivity
Benkercha and Moulahoum [78]	Fault detection and diagnosis	DT (C4.5)	Ambient temperature, irradiation, power ratio	String fault, short-circuit fault, line–line fault	Detection accuracy: 99.87%, Diagnostic accuracy: 99.80%	Limited to the dataset used; real-world performance may vary with different environmental conditions
Harrou et al. [79]	Fault detection	kNN	Residuals from a simulation model, real measurements from a 9.54-kWp PV system	Open circuit, line–line faults, partial shading	High detection accuracy; robust against noise	Performance may vary with different environmental conditions; dependent on accurate simulation models
Hossain et al. [80]	Dust detection	ANN	Optical Sensors	Dust Accumulation	Accuracy: 98.11%	Limited to dust-related issues
Mekki et al. [81]	Partial shading detection	ANNBM (MLP)	Irradiance, Temperature	Partial Shading	Improved fault localization	Limited generalization to diverse faults
Syafaruddin et al. [82]	Fault diagnosis	Three-layer ANN	Irradiance, Temperature, voltage, and current of maximum power point	Short Circuit	Accurate fault localization	Memory-intensive for large systems
Lu et al. [83]	Fault detection	DA-DCGAN	Pre-recorded PV loop current data	Arc faults	Accuracy: 97.68%	Dependency on the quality of generated fake data
Chao et al. [84]	Fault diagnosis	Modified ANN	open-circuit voltage, voltage, current and power of maximum power point	10 faults: Short Circuit, Open Circuit, degraded modules . . .	High fault detection accuracy	Limited generalization due to reliance on simulated data

Table 5. *Cont.*

Study	Approach	AI Technique	Input Data	Fault Type Detected	Key Metrics	Limitations
Akram and Lotfifard [85]	Fault detection and classification	PNN	Irradiance, Temperature, voltage and current of maximum power point	open circuits, line–line faults	Accuracy: 98.53%	Requires extensive labeled data
Zhao et al. [86]	Fault detection and classification	DT	Array Voltage, Current, Temperature, Irradiance	Open/Short Circuit, Line–Line Faults, Partial Shading	99.98% Fault Detection Accuracy, 99.8% Classification Accuracy	High training costs, Challenging to handle unseen faults
Chen et al. [87]	Fault detection and classification	RF	PV-array voltage and each PV-string current at PV's maximum power point	Line–Line Faults, Degradation, Open Circuit, Partial Shading	99.994% Fault Detection Accuracy, 99.952% Classification Accuracy	Requires extensive labeled data, computationally intensive
Madeti and Singh [88]	Fault detection and classification	kNN	Array Voltage, Current, Temperature, Irradiance	Open circuit, line-line faults, partial shading	98.70% Classification Accuracy	Limited to experimental conditions
Zhao et al. [89]	Fault diagnosis	FCM	Open-circuit voltage, Short-circuit current, voltage, current and power of maximum power point	6 faults: Short circuits, shading . . .	Accuracy: 96%	Computational efficiency may vary with dataset size
Lu et al. [90]	Fault diagnosis	CNN + ETSG	PV array voltage and current	Open-circuit faults, line-to-line faults	Accuracy: 99%	May require significant computational resources
Appiah et al. [91]	Fault diagnosis	LSTM	PV array voltage, current and power	line-to-line fault (LLF), and hot spot fault (HSF)	98.78% and 97.66% for HSF and LLF	Performance may depend on data quality and variability
Chen et al. [92]	Fault detection and diagnosis	ResNet	Raw I-V curves, irradiance, and temperature	Short circuits, open circuits, degradation, partial shading	Accuracy: 99.94%	May require extensive training data for optimal performance
Cheng et al. [93]	Fault diagnosis	Data Fusion + Fuzzy Mathematics	Voltage, Current, Temperature, Irradiance, speed of win	Fault localization in large arrays, robust handling of uncertainties	Enhanced accuracy in complex conditions	Computationally intensive
Bonsignore et al. [94]	Fault diagnosis	Neuro-Fuzzy	Irradiance, Temperature, I-V curve parameters	Degraded Modules, Noise Issues	Effective in noisy conditions	Limited scalability

Table 5. *Cont.*

Study	Approach	AI Technique	Input Data	Fault Type Detected	Key Metrics	Limitations
Hempelmann et al. [95]	Fault anomaly detection	VAE	DC voltage, DC current, wind speed, precipitation intensity, temperature, cloud cover, and UV index	Rare faults, unknown faults	92.06% Fault detection rate	High false positives in some cases
Kou et al. [96]	Fault diagnosis	RF + Feature transformation	Three-phase AC current signals	Open-circuit faults in IGBT switches	High accuracy under varying load conditions	Dependent on sensor accuracy and transformation technique
Veerasamy et al. [97]	Fault detection	LSTM	Three-phase current signals	HIFs	Accuracy: 91.21%	Computational cost of LSTM; simulation-based validation
Li et al. [98]	Fault diagnosis	ANN	Measured fault patterns	Open-switch faults	Diagnosis time: 0.5ms, Accuracy: nearly 100%	May not generalize well to unknown converter topologies

This analysis explores different strategies for PV system fault detection and diagnosis, focusing on both UAV-based and sensor-based approaches. UAV-based methods excel in capturing high-resolution imagery and are effective for visual fault detection, but they face challenges such as environmental dependency and limited real-time monitoring capabilities. On the other hand, sensor-based methods provide the advantage of continuous monitoring and real-time fault detection. However, these methods also present computational efficiency, data dependency, and scalability challenges. A horizontal comparison of these approaches reveals that while UAV-based methods are advantageous for large-scale solar installations with their ability to cover extensive areas quickly, sensor-based methods may offer better performance in fault detection with a continuous monitoring system. The choice between these approaches depends on specific application scenarios, such as the scale of the PV system, the importance of real-time monitoring, and the type of faults being targeted.

3.1.2. Predictive Maintenance

Predictive maintenance is a proactive approach that leverages advanced techniques to anticipate equipment failures before they occur, ensuring timely interventions to maintain system efficiency and reliability. In the context of PV systems, predictive maintenance plays a critical role in minimizing system downtime, reducing operational costs, and improving energy output. By analyzing environmental and performance data, AI-based methods, such as ANNs and other statistical models, are capable of forecasting maintenance needs, identifying degradation trends, and detecting anomalies that might lead to potential faults. These approaches represent a significant advancement over traditional reactive or preventive maintenance strategies.

Several studies have demonstrated the application of predictive maintenance techniques in PV systems, showcasing their potential to improve system reliability and optimize maintenance planning.

Riley and Johnson [99] developed a Prognostics and Health Management (PHM) system leveraging ANNs to predict power output based on environmental inputs such

as irradiance, wind, and temperature. The PHM system monitors system health, identifying faults like soiling, degradation, and inverter failures by detecting performance deviations. This approach allows proactive maintenance scheduling and tracks system degradation over time, ensuring long-term reliability and preventing catastrophic failures. De Benedetti et al. [100] proposed an advanced anomaly detection approach combining ANNs and Triangular Moving Average (TMA) analysis to identify long-term degradation trends. Their model compares predicted AC power output, derived from solar irradiance and temperature data, with real-time measurements to detect deviations, issuing alerts that enable maintenance to be scheduled weeks in advance. This method achieved over 90% accuracy in anomaly detection and demonstrated significant potential for reducing power losses and preventing failures. Additionally, Samara et al. [101] introduced a low-cost intelligent monitoring system that employs a compact ANN to predict the standard operational activity of PV panels based on environmental conditions. By comparing predicted performance with actual output, the system detects anomalies that indicate the need for maintenance and automatically notifies administrators or maintenance teams via internet-based alerts. However, the system lacks functionality for isolating or removing malfunctioning panels.

Extending these efforts, Huuhtanen and Jung [102] applied CNNs to predictive maintenance by analyzing power output curves of panels. Their method predicted the daily power curve of a target panel using neighboring panels' power curves, flagging large deviations as indicators of malfunction. By addressing challenges like dynamic weather variations and regular shadowing, the unshared convolutional model demonstrated superior performance, showcasing the potential of CNNs for accurate anomaly detection in PV systems. Betti et al. [103] further advanced predictive maintenance strategies by introducing a big data-driven framework for PV plants. Their dual-model architecture combined a Supervision-Diagnosis Model (SDM), which employed Self-Organizing Maps (SOMs) for detecting operational deviations, and a Short-Term Fault Prediction Model (FPM), which utilized a Pattern Recognition Neural Network (ANN) to forecast specific fault classes. Tested on six PV plants, the system demonstrated the ability to predict faults up to 7 days in advance with high sensitivity and specificity, enhancing reliability and reducing downtime.

To address the scalability challenges of large PV plants, Zulfauzi et al. [104] proposed a hybrid ML approach integrating K-Means clustering and LSTM networks. The K-Means algorithm clustered operational patterns based on meteorological data, while LSTM accurately predicted deviations in electrical currents for precise anomaly detection. This hybrid approach demonstrated superior performance over conventional ANN models, offering a scalable and cost-effective solution for predictive maintenance in large-scale PV systems. Similarly, Marangis et al. [105] developed a data-driven routine combining XGBoost, One-Class SVM, and the Facebook Prophet algorithm. Their methodology analyzed performance trends to generate predictive maintenance alerts up to 7 days in advance. Validated on a 1.8 MW PV power plant, the system achieved a sensitivity of 92.9% and a predictive accuracy of 99.4%, demonstrating its robustness in detecting underperformance conditions such as inverter shutdowns and string disconnections.

Table 6 provides a comparative overview of these studies, highlighting their methodologies, data requirements, fault types addressed, key contributions, and limitations.

Table 6. Comparative table for predictive maintenance in PV systems.

Study	Approach	AI Technique	Data Inputs	Fault Type	Key Contributions	Limitations
Riley & Johnson [99]	Predict power output to identify faults.	ANN	Irradiance, wind, temperature	Soiling, degradation, inverter failures	Tracks system degradation over time; ensures long-term reliability; proactive maintenance scheduling.	Requires system-specific training data; limited scalability to different PV configurations.
De Benedetti et al. [100]	Compare predicted vs. real-time output to detect anomalies and schedule maintenance weeks in advance.	ANN + TMA	Irradiance, temperature, AC power output	Long-term degradation trends	Predictive alerts weeks ahead; 90%+ anomaly detection rate; 2.3% validation error; low-complexity model; detects degradation trends.	Relies on specific datasets; potential challenges in handling dynamic weather conditions.
Samara et al. [101]	Predict standard operational activity; send internet-based alerts for anomalies.	ANN	Environmental conditions, panel output	General anomalies	Low-cost intelligent monitoring; real-time anomaly detection; automated alert system.	Cannot isolate or remove malfunctioning panels; lacks advanced classification of fault types.
Huuhtanen & Jung [102]	Predict target panel output using neighboring data; flag deviations for anomalies.	CNN	Power output curves of neighboring panels	Dynamic weather-induced faults, shadowing	Addresses weather variations and shadowing; superior accuracy with unshared CNN model; uses synthetic and real-world data.	Requires extensive training data; potential issues with highly dynamic environmental changes.
Betti et al. [103]	Dual-model architecture: SOM for generic deviations and ANN for fault classification.	SOM + ANN	SCADA data	Generic deviations, inverter faults	Predicts faults 7 days in advance; scalable to large PV systems; reduces downtime and enhances reliability.	Needs large historical data for training; limited fault class taxonomy in its current implementation.
Zulfauzi et al. [104]	Cluster similar patterns and predict deviations in current to detect anomalies.	K-Means + LSTM	Module output currents, irradiance, temperature	Electrical anomalies (current deviations)	Hybrid model achieves superior accuracy; scalable to large PV systems; cost-effective for predictive maintenance.	Complexity in integrating clustering and time series models; potential limitations with very large datasets.

Table 6. *Cont.*

Study	Approach	AI Technique	Data Inputs	Fault Type	Key Contributions	Limitations
Marangis et al. [105]	Predict performance trends and detect underperformance conditions using advanced statistical and ML techniques.	XGBoost + One-Class SVM + Prophet	Current, voltage, performance data (trends)	Inverter shutdowns, string disconnections	High sensitivity (92.9%) and accuracy (99.4%); detects specific conditions like inverter shutdowns and string disconnections.	May require additional resources for deployment in diverse climatic conditions; scalability to very large systems is untested.

The reviewed predictive maintenance approaches for PV systems highlight a shift toward AI-driven fault detection and performance optimization strategies. These methods, ranging from ANN-based models for anomaly detection to advanced hybrid models incorporating deep learning and ensemble techniques, show promising results in identifying faults before failures occur. However, the reliance on specific datasets and system configurations limits their generalizability. Future research should focus on developing adaptable models capable of handling diverse environmental conditions and PV setups while integrating robust fault isolation mechanisms. The trade-off between model complexity and predictive accuracy requires consideration of data dependencies, scalability, and computational resources. Hybrid models and scalable architectures offer potential solutions for improving the applicability and efficiency of predictive maintenance in PV systems.

3.1.3. Energy Forecasting and Optimization

Accurately forecasting solar energy production and optimizing energy management are vital for enhancing the efficiency and reliability of PV systems. Researchers have explored diverse methodologies to address these challenges, leveraging advanced machine learning techniques, hybrid models, and optimization frameworks. A wide range of studies has focused on improving forecasting accuracy, handling weather variability, optimizing energy dispatch, and managing uncertainties, with approaches varying across different forecasting horizons.

Early efforts to improve forecasting accuracy include the work of Huang et al. [106], who compared physical models and neural network (NN)-based statistical models for day-ahead PV power forecasting. Their study demonstrated the superior performance of NN models, achieving a normalized Root Mean Square Error (nRMSE) of 10.5%, compared to 12.45% for physical models. Similarly, Paoli et al. [107] employed ANNs with time series preprocessing to predict day-ahead solar irradiation, reducing forecasting errors by 5–6% compared to traditional methods such as ARIMA. For short-term predictions, Dahmani et al. [108] focused on a 5 min forecasting model for tilted surfaces, achieving high accuracy with an nRMSE of 8.81%. These studies highlighted the importance of high-quality input data and preprocessing techniques for achieving reliable predictions. Brofferio et al. [109] contributed to improving forecasting accuracy by introducing a hybrid Estimation Model (EM) using Adaptive Resonance Theory (ART) neural networks. This model refined power predictions from single-diode models, enhancing accuracy for nonlinear system behavior. Saberian et al. [110] compared General Regression Neural Networks (GRNNs) and Feedforward Backpropagation Neural Networks (FFBP) for solar power forecasting, finding FFBP to outperform GRNNs in terms of accuracy when predicting power output from temperature and irradiance data. Building on these foundational works, Pedro and Coimbra [111] introduced a short-term solar irradiance forecasting framework

using optimized kNN and ANN models. Their approach incorporated feature extraction techniques to improve forecasting for time horizons ranging from 15 min to 2 h. Ramsami and Oree [112] proposed a hybrid method for forecasting the 24 h ahead energy output of PV systems based on daily weather forecasts. Their approach integrates stepwise regression to identify the most significant meteorological variables, which are then used as inputs for three single-stage models: GRNN, feedforward neural network (FFNN), and multiple linear regression (MLR). The hybrid models demonstrated superior performance compared to their single-stage counterparts, with the stepwise regression–feedforward neural network (SR-FFNN) model achieving the best results. In contrast, Bouquet et al. [113] applied LSTM models to forecast PV power output across multiple time horizons, ranging from 15 min to several days, improving grid stability and reducing dependency on non-renewable energy.

Weather variability remains a significant challenge in solar energy forecasting. Sivaneasan et al. [114] tackled this issue by integrating fuzzy logic preprocessing with ANN models to classify weather changes and introduced an error correction mechanism for 5 min short-term forecasts. Wang et al. [115] further addressed weather-related challenges by combining GANs with CNNs to augment weather datasets and improve day-ahead predictions. Similarly, Lu and Chang [116] proposed a hybrid Radial Basis Function Neural Network (RBFNN) and Grey Theory model for day-ahead forecasts, enhancing forecasting precision by improving data regularity. Ling et al. [117] advanced this area by introducing HCISEM-GAN, a real-time solar energy management system that combines GANs with Human–Computer Interaction to achieve a 20% improvement in prediction accuracy.

In the context of energy dispatch and load management, Wen et al. [118] proposed a DRNN-LSTM model for forecasting residential load and PV output in microgrids. This model enabled optimal energy dispatch by integrating PV forecasts with energy storage systems (ESS) and electric vehicles (EVs), reducing peak loads and operational costs by 8.97%. Similarly, VanDeventer et al. [119] utilized a Genetic algorithm–Support Vector Machine (GASVM) framework to optimize short-term PV power predictions, achieving significant reductions in RMSE and MAPE errors.

Efforts to enhance solar panel performance have also contributed to the field. Shirbhate and Barve [120] developed a Hidden Markov Model (HMM)-based approach for predicting solar energy generation using time series meteorological data. Their system optimized smart solar system performance by capturing the probabilistic correlation between past and future values, closely replicating actual power output. Sujatha et al. [121] employed ANN models to estimate azimuth angles for solar tracking, optimizing panel orientation under various weather conditions. Additionally, Tharakan et al. [122] developed a dual-axis solar tracker based on the Naive Bayes algorithm to predict optimal panel orientation, significantly increasing energy harvesting efficiency.

Addressing uncertainties in PV energy forecasting has been another area of focus. Sharifzadeh et al. [123] conducted a comparative analysis of ANNs, Support Vector Regression (SVR), and Gaussian Process Regression (GPR), finding ANNs to be the most accurate model despite challenges in parameter optimization. Galván et al. [124] proposed a multi-objective approach using neural networks combined with Multi-Objective Particle Swarm Optimization (MOPSO) to optimize prediction intervals, minimizing interval width while maximizing coverage probability. This method provided a reliable balance between prediction accuracy and uncertainty reduction, though it faced computational challenges due to the evolutionary optimization process. Al-Omary et al. [125] further improved ANN-based forecasting by optimizing input features and network structure, achieving prediction errors below 2%. Kaur et al. [126] proposed a VAE-Bayesian BiLSTM framework to quantify uncertainties and enhance reliability, demonstrating its potential for managing variability in energy predictions.

Table 7 provides a comparative overview of these studies, highlighting their methodologies, forecasting horizons, data requirements, key contributions, and limitations.

Table 7. Comparative analysis of related works in energy forecasting and optimization.

Study	Approach	Forecasting Horizon	AI Technique	Data Inputs	Key Contributions	Limitations
Huang et al. [106]	Comparison of physical models and NN-based statistical models	Day-ahead	Neural Networks	Solar irradiance, air temperature, cloud cover, humidity	Demonstrated NN models' superiority with nRMSE of 10.5% over physical models' 12.45%; real-time correction potential.	Sensitive to weather variability and relies on NWP data quality.
Paoli et al. [107]	Daily prediction of global solar radiation on a horizontal surface	Day-ahead	ANN	Clearness indices, solar radiation time series	Improved accuracy by 5–6% over traditional models like ARIMA; nRMSE = 37% (winter), 15% (summer); $R^2 > 0.99$ validation.	Dependent on high-quality time series data.
Dahmani et al. [108]	Developed a MLP model of solar-tilted global irradiation from horizontal ones	Short-term (5 min)	ANN (MLP)	Horizontal irradiation, declination, zenith, azimuth angles	Achieved high accuracy (nRMSE of 8.81%) for tilted surfaces; input sensitivity; validated on 2-year dataset.	Limited generalizability to different regions and inclinations.
Brofferio et al. [109]	Estimating and monitoring the power generated by a PV module	Day-ahead	ART	PV power data, system parameters	Enhanced accuracy for nonlinear PV system behavior; real-time monitoring; tested on 1-year data.	Requires high-quality system-specific data for accurate estimates.
Saberian et al. [110]	Comparison of GRNN and FFBP for solar power output forecasting	Day-ahead	GRNN, FFBP	Temperature (max, min, mean), solar irradiance	FFBP showed superior accuracy compared to GRNN.	Limited scalability for larger datasets or variable conditions.
Pedro and Coimbra [111]	Feature extraction with kNN and ANN models for short-term solar irradiance forecasting	Short-term (15 min–2 h)	kNN + ANN	Historical Global Horizontal Irradiance (GHI), variability metrics	Outperformed persistence-based models for short-term predictions; RMSE = 20–60 W/m^2 depending on site.	Computational complexity due to feature optimization.

Table 7. *Cont.*

Study	Approach	Forecasting Horizon	AI Technique	Data Inputs	Key Contributions	Limitations
Ramsami and Oree [112]	A hybrid method for 24 h ahead PV energy forecasting.	Day-ahead	GRNN, FFNN, MLR	Meteorological data (temperature, irradiance, wind)	RMSE range: 2.65–3.22; Monthly % error: as low as 0.1% (SR-FFNN), up to 6.7% (MLR).	Model simplicity may limit accuracy improvements for complex environments.
Bouquet et al. [113]	Multi-horizon solar power forecasting	Multi-horizon (15 min–7 days)	LSTM	Historical PV power output, meteorological data	Enhanced grid stability and reduced reliance on non-renewable energy sources; 95% Confidence intervals.	Computationally intensive for multi-horizon scenarios.
Sivaneasan et al. [114]	Classification of weather changes	Short-term (5 min)	ANN with Fuzzy Logic	Cloud cover, temperature, wind speed, solar irradiance	MAPE improvement: Up to 52.48% on specific days; low-data capability.	Relies on high-quality weather data for meaningful classification.
Wang et al. [115]	Weather data augmentation and solar forecasting	Day-ahead	GAN + CNN	Weather data (temperature, irradiance, cloud patterns)	Overall Accuracy up to 76.9%; Data augmentation gain: accuracy increased 4.2–21.3% across models.	Computational cost due to GAN and CNN training processes.
Lu & Chang [116]	Hybrid model for day-ahead PV forecasting	Day-ahead	RBFNN + Grey Theory	Meteorological data (temperature, radiation, cloud cover)	MAPE = 3.71%; RMSPE = 4.65%; More accurate and computationally efficient than all baseline models.	Preprocessing steps may limit real-time applicability.
Ling et al. [117]	Real-time solar energy management	Multi-horizon	HCISEM-GAN	Meteorological data (irradiance, temperature, cloud cover)	Quicker decision-making; 96% user response accuracy; 98% navigation efficiency; 97% Implementation Success.	Relies heavily on GAN training quality and user input for adjustments.
Wen et al. [118]	Short-term residential PV output and load forecasting in microgrids	Short-term	DRNN + LSTM	Aggregated residential PV output, load data, meteorological parameters	Enabled energy dispatch with ESS and EV scheduling, reducing peak loads by 8.97%; MAPE = 7.43%.	Limited to microgrid setups with specific configurations.

Table 7. *Cont.*

Study	Approach	Forecasting Horizon	AI Technique	Data Inputs	Key Contributions	Limitations
VanDeventer et al. [119]	Hybrid model for short-term PV forecasting	Short-term	SVM + GA	Meteorological data (temperature, irradiance), PV power	RMSE improved by 669.624 W; MAPE improvement: 98.76%.	Computationally expensive due to the optimization process.
Shirbhate and Barve [120]	Hidden model for predicting solar energy generation in smart solar systems	Short-term	HMM	Meteorological data (temperature, humidity, irradiance)	Optimized smart system operation with time series probabilistic modeling.	Limited generalization for complex systems with diverse configurations.
Sujatha et al. [121]	ANN-based solar tracking system to estimate azimuth angles and optimize panel orientation	Short-term	ANN	Sun position data (azimuth angles), weather conditions (sunny/cloudy)	Improved energy efficiency by optimizing solar panel orientation under varying weather conditions.	Limited to local weather data; requires astronomical calculations for sun position estimation.
Tharakan et al. [122]	Machine learning-based dual-axis solar tracker for optimal panel orientation	Short-term	Naive Bayes algorithm	LDR sensor data, solar panel angles, environmental conditions	Significantly improved energy harvesting efficiency with automated orientation adjustments.	Limited applicability to systems without dual-axis tracking infrastructure.
Sharifzadeh et al. [123]	Comparative analysis for renewable energy forecasting	Day-ahead	ANN, SVR, GPR	Weather data (irradiance, temperature)	Demonstrated superior accuracy of ANNs for solar energy forecasting.	Challenges in parameter optimization for specific conditions.
Galván et al. [124]	Multi-objective optimization of prediction intervals	Day-ahead	Neural Networks, MOPSO	Meteorological data (temperature, radiation, cloud cover)	Balanced interval width and reliability; adaptable to user needs via Pareto fronts; MOPSO maintains high accuracy.	High computational cost due to evolutionary optimization.
Al-Omary et al. [125]	Cascaded input/structure optimization for ANN-based solar energy prediction	Day-ahead	ANN with Optimization	Air temperature, humidity, zenith angle	Achieved prediction errors below 2%, optimizing network structure for high accuracy.	Limited scalability to highly variable datasets.
Kaur et al. [126]	Probabilistic solar power forecasting	Multi-horizon	Bayesian BiLSTM + VAE	Historical PV output, meteorological data	Quantified uncertainties and improved prediction reliability for smart grids; improved R-score; Fast convergence.	Complexity in training Bayesian models and VAE integration.

These studies collectively highlight significant advancements in PV energy forecasting, focusing on improving accuracy, optimizing energy dispatch, and managing uncertainties. Integrating advanced AI techniques and hybrid models has enhanced the ability to handle weather-induced variability, temporal dependencies, and energy storage optimization. Short-term forecasting, in particular, benefits from neural networks and hybrid architectures such as LSTM, GANs, and ART-based models, which outperform traditional statistical methods. Long-term and day-ahead predictions are strengthened through model ensembles and feature selection techniques, improving robustness and generalizability. Despite these advancements, challenges such as computational complexity, reliance on high-quality data, and scalability persist. Energy dispatch optimization increasingly integrates forecasting with storage and demand-side elements (e.g., ESS, EVs), illustrating a shift toward more comprehensive energy management systems. However, practical constraints remain, especially for real-time applications.

3.2. Applications of IoT in PV Systems

With the growing adoption of solar energy as a key renewable resource, the need for smarter, more efficient PV systems has become paramount. IoT technologies have paved the way for innovative solutions tailored to the unique challenges faced by PV systems, such as real-time monitoring, maintenance optimization, energy management, solar tracking, and fault detection. This section delves into specific applications of IoT in PV systems, showcasing how these technologies are driving advancements in automation, performance optimization, and system reliability.

3.2.1. Solar Monitoring Systems

Solar monitoring systems track real-time data from PV systems, such as solar irradiance, temperature, and power output, to optimize performance. By identifying issues and predicting maintenance needs, these systems ensure efficient and reliable solar energy production. IoT integration enables remote monitoring and proactive maintenance.

Several studies focus on IoT-based monitoring and control of solar PV systems. In 2020, Mubashir Ali and Mahnoor Khalid Paracha [127] proposed an IoT system that automatically monitors and controls parameters such as voltage, current, and power consumption, sending real-time data to users. The authors enabled users to monitor and control solar panels via their mobile devices, providing an efficient way for users to manage their systems remotely. Also, Aghenta et al. [128] present a low-cost, open-source SCADA system for monitoring and remote control of solar PV systems, based on IoT architecture. It uses analog current and voltage sensors for data acquisition, an Arduino Uno microcontroller for data reception, and a Raspberry Pi with Node-RED for data parsing. The system stores and monitors data using the Emoncms IoT platform. The developed SCADA system was tested on a 260W solar PV panel, and its data are accessible via dashboards on a cloud server, allowing monitoring through both a computer and a mobile app. Gupta et al. [129] propose in their paper an IoT-based solar metering system designed for remote monitoring and analysis of solar setups. The system allows real-time monitoring of solar output, enabling quick identification of any interruptions. It is particularly suitable for remote areas where solar energy is abundant but access is limited and cost-prohibitive. The system uses a Raspberry Pi, MCP3008 (Analog to Digital Converter), DC Voltage Transducer, and a current shunt. The system is developed using the Virtual Instrument Programming Language (LabVIEW), providing an efficient solution for monitoring and managing solar power in remote locations. In 2021, Gupta et al. also [130] presented a low-cost, IoT-based data acquisition system (DAQ) for PV monitoring, designed to withstand harsh environmental conditions. Tested over 28 days, the system effectively gathers operational data, detects

performance degradation, and features Wi-Fi-controlled switches for remote operation, reducing energy consumption by 58%. The study also highlights a 13% decline in PV module output due to dust accumulation, emphasizing the importance of maintenance. Furthermore, Pereira et al. [131] propose a Renewable Energy Monitoring System (REMS), which is a real-time cloud monitoring solution for decentralized PV plants. It utilizes Raspberry Pi and IoT technologies to measure PV voltage, current, module and ambient temperature, solar irradiance, and humidity. REMS features remote firmware updates via a custom Analog/Digital Converter Embedded System and communicates with a tailored cloud server using an RPi Embedded Linux System, eliminating the need for a dedicated PC. Shapsough et al. [132] propose an IoT-based architecture for real-time monitoring and management of large-scale solar PV systems. The system enables remote control and monitoring of solar plants while assessing environmental factors like weather, air quality, and soiling. It uses MQTT for efficient, wide-scale communication with minimal network delay (under 1 s) and low resource consumption (around 3% of the panel's output). The evaluation concludes that this architecture is ideal for deployment with low-cost edge devices, offering a scalable, cost-effective solution for solar and smart grid monitoring systems. Using MQTT and Modbus, Lakshmi et al. [133] focus on their project on using solar power to operate an agricultural motor pump. A Variable Frequency Drive (VFD) controls the motor pump, with solar power as the input to the VFD. The project also involves developing a Remote Monitoring System (RMS) that reads data from the VFD controller, including solar power and motor pump values. The RMS uses MODBUS communication to collect these data and sends them to a web server using the MQTT protocol. GPS tracking is employed to determine the motor pump's installation location, and GSM technology allows the motor pump to be turned on or off via SMS or call. Real-time data, such as the motor pump's status, frequency, power, voltage, speed, and temperature, can be accessed on the web server anytime. Deenadayalan et al. [134] propose an embedded system for remote monitoring of inverters in a solar power plant. The system uses a Raspberry Pi as the controller, with inverters connected in a daisy chain and the final inverter linked to the Raspberry Pi. Key data, such as total power and failsafe parameters (grid fault, PV over, over current, over temperature, and short circuit), are obtained via the Modbus protocol. Additionally, sensors measure temperature, wind speed, and solar irradiance. These data are uploaded to an SQL database over Wi-Fi, and users can remotely monitor the system through a web interface, allowing access to real-time performance data of the solar power plant. Also, Gimeno et al. present in article [135] a practical and low-cost monitoring system for photovoltaic water pumping systems (PVWPSs) that use lithium-ion batteries. With the increasing use of PV technology and falling battery prices, integrating energy storage into solar-powered systems is becoming more common. The work proposes a quasi-real-time monitoring solution using open-source IoT tools to help manage, operate, and develop these systems more effectively. The system was tested using a setup that includes a solar field, a hybrid inverter, a lithium-ion battery, a variable speed driver, and a submersible pump. Data are collected using commercial hardware with Modbus-RTU communication and processed through a Raspberry Pi. Data is stored in InfluxDB and visualized using Grafana, while a customizable exporter allows users to create Excel or .csv files of selected data. This system shows how IoT and open-source tools can enhance the performance and monitoring of solar energy systems. Using the PROFINET protocol, Mohammed et al. [136] outline the development of a real-time solar panel monitoring system using a web server and a Siemens S7-1200 PLC, programmed with TIA Portal V17. The system collects key data—voltage, current, power output, temperature, irradiance, and environmental conditions—and transmits them to a web server via the PROFINET protocol for wired communication between the PLC and client devices. Users can access these

data remotely through a web browser over WIFI to monitor performance, view historical trends, and receive alerts for any issues. This setup enhances solar energy management by enabling efficient monitoring, quick issue detection, and informed decision-making for maintenance and optimization. Karthick et al. [137] present a low-cost energy monitoring system for solar PV setups that uses wired communication through RS-485, a standard industrial protocol. The system integrates an RS-485-to-Serial Converter to collect real-time data from an energy meter and transmit it to an ESP32 microcontroller. This wired communication ensures reliable data transfer between components, making it suitable for consistent monitoring in PV systems. Meanwhile, in their paper, Calderon et al. [138] explore how Industrial Internet of Things (IIoT) and Industry 4.0 concepts can be applied in real-life setups, not just in theory. They demonstrate a low-cost practical implementation of an IIoT architecture designed to enhance energy systems, including PV sources. Unlike many works focusing only on theoretical models, their approach is experimentally validated through a pilot microgrid setup combining solar and hydrogen energy. The proposed system is structured into four functional layers: Sensing, Network, Middleware, and Application. The application layer leverages Grafana for real-time visualization and remote access via the web. This architecture effectively shows how IoT tools can be integrated into PV monitoring systems to improve data accessibility, operational transparency, and system scalability in modern smart energy environments. On the other hand, Kodali and John [139] describe solar monitoring systems that utilize a microcontroller and sensors to collect data, which are then transmitted to clients via Amazon Web Services (AWS). The incorporation of IoT in these systems enhances the efficiency of solar energy usage. In paper [140], Paredes et al. introduce a low-cost wireless solution using LoRa technology for monitoring PV power plants. The system offers long-range communication with minimal power usage, integrating open-source sensors and LPWAN for efficient IoT-based data exchange. It highlights the system's application in real PV installations and assesses its performance in grid-connected environments. In their study, Al-Naib (2023) [141] introduces a real-time data acquisition and monitoring system for PV panels using IoT technology, specifically employing a Siemens S7-1200 PLC. The system collects data from multiple sensors, including voltage, current, temperature, and irradiance, and sends this information to a cloud platform (Ubidots) for remote monitoring. Three visualization methods were utilized: SIMATIC WinCC for local monitoring, Excel for data logging, and Ubidots for online access. Tested in Kirkuk, Iraq, the system demonstrated high accuracy and reliability over a 10 h period, showing its potential for scalable, low-cost PV monitoring in remote locations. Similarly, Spanias [142] developed an IoT-based system to enhance the efficiency and functionality of solar array farms by enabling real-time monitoring of solar energy. Many countries have contributed to this field; for example, Japan developed a first-generation smart monitoring device (SMD) equipped with IoT-enabled panels. The proposed model uses sensors and PV arrays, relying on advanced vision and fusion algorithms. This innovative approach introduces a new generation of solar array farms, incorporating mobile analytics to identify faults, benefit users, and perform continuous optimization, thereby improving operational quality. It also aids in power prediction and provides robust monitoring capabilities.

Several works incorporate predictive models and fault detection to enhance solar panel efficiency. Shweta et al. [143] propose an IoT-based control and monitoring solution for a grid-connected hybrid solar power system. It automatically detects and prevents PV faults to avoid damage and maintain system performance. Fault detection is handled by an Arduino-based system using voltage, current, and temperature sensors, and a fuzzy nonlinear autoregressive exogenous model classifies faults. The system ensures reliable power delivery and grid stability, validated through real-time implementation and simulations. In

their study, Kekre et al. [144] present a low-cost IoT-based embedded solar PV monitoring system that leverages a GPRS module and a microcontroller to transmit real-time data to the internet. The system enables global access to production metrics, facilitating maintenance, fault detection, and comprehensive data logging at regular intervals. Similarly, Adhya [145] introduces a cost-effective IoT-based methodology for remote monitoring of PV plants, enabling real-time performance evaluation with Wi-Fi, preventive maintenance, fault detection, and historical data analysis. The approach leverages web-based interfaces to automate plant monitoring and ensure operational efficiency even in challenging locations. Emamian et al. [146] propose an Intelligent Monitoring System (IMS) for PV systems using IoT technology. The system enables real-time monitoring, fault detection, and power prediction through a personal cloud server and a web-based interface. It is scalable, cost-effective, and designed for easy deployment, ensuring continuous monitoring and performance optimization of PV plants. Additionally, Shakya et al. [147] propose in their paper an algorithm that uses IoT and data-mining techniques to monitor power generation and detect faults in solar power systems. The algorithm helps identify areas of failure or defects, enabling quick corrective actions to improve the efficiency of large-scale solar power stations. Suresh et al. [148] researched an IoT-based system for monitoring power generation, efficiency, and other key parameters in solar panels to minimize breakdowns and faults, thereby enhancing efficiency. Effective monitoring and maintenance of PV solar panels are crucial for preserving system integrity and sustaining optimal efficiency. Del Río et al. [149] propose an IoT platform for PV maintenance, utilizing classification algorithms to detect performance ratio patterns. A case study using SCADA data from a Spanish solar plant applies Shapelets and k-nearest neighbors (KNN), with KNN preferred for its faster execution. The platform improves PV maintenance by enabling timely intervention through performance monitoring. Also, Kingsley et al. [150] present an IoT-based system for fault detection and analysis in solar PV systems. The system effectively identifies, classifies, and analyzes faults in real time, ensuring 98.95% accuracy. Real-time data collection at both fog and cloud levels enhances fault detection reliability, achieving 100% data communication integrity and 98% availability. Mellit et al. [151] developed a prototype device for fault detection in stand-alone solar power systems using an internet-based approach. The system tracks real-time data on electrical output, air temperature, and sunlight levels via a web application. It identifies faults such as open circuits, shading, and dust accumulation on solar panels, providing user notifications. The prototype is cost-effective, easy to install, and requires no additional components or complex setup. Li et al. [152] present an IoT-based PV monitoring system focused on fault detection and maintenance. Using the TMS320F28335 DSP and ZigBee communication, the system collects and transmits data to a gateway, which also captures geographic and visual information. A PV monitoring website displays real-time data and employs an Extreme Learning Machine (ELM) for fault diagnosis, achieving 97.5% accuracy. Users receive fault alerts via email, ensuring timely maintenance and improved system reliability. As well, Xia et al. [153] propose an IoT-based real-time monitoring system for PV fault detection and maintenance. Utilizing ZigBee for node communication and 4G for cloud transmission, the system processes operational data using a Probabilistic Neural Network for fault diagnosis. It enables remote monitoring via web and mobile interfaces, diagnosing faults in DC output, AC output, and power generation. By leveraging cloud diagnostics, the system reduces local device costs while ensuring efficient fault detection and maintenance. Nalamwar et al. [154] developed an IoT-based system for real-time fault detection and automated control of solar panels. Equipped with sensors and block management modules, the system continuously monitors electrical data, identifies faults, and sends maintenance alerts. Additionally, it adjusts panel orientation based on sunlight direction, minimizing human intervention

and enhancing operational efficiency. In their study, Hamied et al. [155] present a smart IoT-based remote sensing prototype for fault detection and identification in PV arrays. It uses voltage, current, and temperature sensors to incorporate a system with an automated fault detection algorithm capable of identifying issues such as open circuits, short circuits, dust accumulation, and shedding effects. Tested at the Renewable Energy Laboratory of Jijel University, Algeria, the prototype demonstrated effective remote monitoring and fault identification. Users can check the system status online via a website, with IoT-enabled notifications also sent via SMS.

Several studies have focused on IoT-based monitoring systems that track both solar power generation and environmental conditions to enhance performance and ensure efficient operation. Shirbhate and Barve [120] aimed to develop a smart IoT solar system capable of capturing the optimal amount of solar energy and generating power based on meteorological data, while also predicting various other factors. They employed the Hidden Markov Model (HMM) for prediction, considering the probabilistic correlation between past and future values in time series data. The results showed that by deploying a single panel dead state, the system was able to accurately predict solar energy generation based on time series data, closely reproducing actual power output. Similarly, W Priharti et al. [156] propose a remote and real-time monitoring system for solar PV systems using IoT to address performance variability due to environmental conditions. This IoT-based system is structured into three main components: data acquisition, a data gateway, and a smartphone application display. Data acquisition is highly accurate, achieving 98.49% accuracy in capturing data, which is then transmitted through the data gateway. The gateway effectively relays the data to the smartphone app, allowing users to view graphical representations with a mean transmission time of 52.34 s. Cheddadi et al. [157] present a cost-effective, open-source IoT solution for real-time monitoring of solar power generation and environmental conditions. Designed as a laboratory prototype, the system can be easily extended for large-scale PV stations with minimal adjustments. It also includes an alert feature that notifies remote users when solar power generation quality deviates from predefined standard values.

Various studies have explored dust monitoring systems for PV installations, emphasizing their role in detecting dust accumulation and ensuring optimal performance through timely maintenance. In their study, Malik et al. [158] focus on reducing energy losses in PV systems caused by dust deposition. The proposed solution leverages an IoT-based framework with a modular design. Each module uses an embedded controller to monitor the status of individual PV panels, and the data are sent to a cloud system for real-time analysis. An automatic maintenance decision algorithm processes the open-circuit voltage values of the panels to determine when maintenance is necessary. This system helps ensure optimal performance throughout the PV system's lifecycle by enabling timely maintenance actions. The prototype successfully met its objectives. Narivos et al. [159] propose an IoT-based system that was developed to monitor dust accumulation on solar panels and automatically trigger a cleaning system when necessary. The system uses a dust sensor to detect and monitor the amount of dust on the panels. Once the accumulated dust reaches a certain threshold, the cleaning mechanism is activated. Additionally, ambient temperature and humidity are monitored using sensors, and the data are transmitted via the Blynk IoT platform.

In the study by Ul Mehmood et al. [160], a cloud-based Solar Conversion Recovery System (SCRS) was developed, integrating IoT technology for remote monitoring of PV panel soiling. The system used low-cost sensors and an Artificial Neural Network to optimize scalability and reduce hardware requirements. Multiple ANN models were tested, with the most effective configuration achieving a mean squared error of 0.0117 and an R^2 of 0.905. Data from soiling stations were transmitted wirelessly using the MQTT protocol,

eliminating the need for extra wiring. The system's average error rate in estimating the soiling ratio was 4.33%.

Furthermore, the limited lifespan of rechargeable batteries poses a challenge for IoT devices and their applications, as they cannot ensure a constant power supply over time. To address this issue, Adila et al. [161] propose a solution focused on energy harvesting through an interconnected network of devices drawing power from their surroundings. The paper demonstrates how energy harvesting can efficiently provide a continuous battery power supply, even for low-powered devices, ensuring sustained operation even over varying distances. Table 8 presents a comparative analysis of the mentioned IoT-based solar PV monitoring systems highlighting the IoT technology used, data acquisition methods, communication protocols, key monitoring features, and cost-effectiveness.

Table 8. Comparative analysis of IoT-based solar PV monitoring systems.

Study	IoT Technology Used	Data Acquisition	Communication Protocol	Monitoring Features/Additional Functions	Low Cost
Mubashir Ali and Mahnoor Khalid Paracha [127]	IoT system with mobile interface	Voltage, current, power	Wireless	Remote monitoring and control via mobile devices	No
Aghenta et al. [128]	Open-source SCADA system	Analog current and voltage sensors for PV data	Wireless	Remote monitoring via cloud-based dashboards	Yes
Gupta et al. [129]	IoT solar metering system	DC Voltage Transducer, Current Shunt	Wi-Fi	Remote monitoring for off-grid solar setups	Yes
Gupta et al. [130]	IoT-based DAQ system	Current, voltage, humidity, temperature, wind speed, dust	Wi-Fi	Energy-saving switches; 58% power saving and 13% PV degradation analysis	Yes
Pereira et al. [131]	Renewable Energy Monitoring System (REMS)	Solar voltage, current, temp, irradiance	Wi-Fi	Remote firmware updates and real-time cloud monitoring	No
Shapsough et al. [132]	MQTT-based IoT architecture	Environmental conditions, PV efficiency	MQTT	Low-cost, real-time monitoring with <1 s network delay	Yes
Lakshmi et al. [133]	IoT-based monitoring system for solar-powered motor pump	status, frequency, power, voltage, speed, temperature	MQTT, MODBUS	Real-time monitoring of motor pump, remote control via SMS/call, GPS tracking for installation location	Yes
Deenadayalan et al. [134]	Embedded monitoring for solar inverters	Grid fault, PV over/under voltage	Modbus, Wi-Fi	Remote monitoring of inverter performance via web platform	No
Gimeno et al. [135]	Open-source IoT tool-based monitoring system	Voltage, current, power, battery status	Modbus-RTU (wired)	Quasi-real-time monitoring, data stored in InfluxDB, visualized using Grafana, customizable exporter for Excel/CSV files	Yes
Mohammed et al. [136]	Siemens S7-1200 PLC-based IoT monitoring system	Voltage, current, power, temperature, irradiance, environmental conditions	PROFINET (wired)	Real-time monitoring, web server access via WiFi, performance tracking, and issue alerts for maintenance and optimization	No

Table 8. *Cont.*

Study	IoT Technology Used	Data Acquisition	Communication Protocol	Monitoring Features/Additional Functions	Low Cost
Karthick et al. [137]	ESP32 microcontroller based energy monitoring system	real-time energy production	RS485 (wired)	real-time energy production suitable for consistent PV system monitoring	Yes
Calderon et al. [138]	Industrial IoT architecture (IIoT), Grafana for GUI	Temperature, voltage, current, irradiance	PROFINET, Modbus TCP and HTTP	Remote web-based monitoring with Grafana, application in real microgrid with energy management	Yes
Kodali and John [139]	IoT-based monitoring system	Microcontroller and sensors	Wireless (AWS)	Enhanced solar energy usage via cloud services	No
Paredes et al. [140]	IoT-based monitoring system	PV electrical data, weather conditions	LoRa (LPWAN)	Long-range communication with low power consumption, real-time monitoring in IoT environment	Yes
Al-Naib [141]	Real-time IoT monitoring system with Siemens S7-1200 PLC	Voltage, current, temperature, irradiance	Wireless	Multi-platform monitoring with high reliability	No
Spanias [142]	IoT-enabled solar array farms	Voltage, current, temperature, irradiance	Wireless	Advanced vision and fusion algorithms for fault prediction	No
Shweta et al. [143]	IoT-based control and monitoring system	Voltage, Current, Temperature	Wireless	Automatic fault detection, power quality improvement, grid stability	Yes
Kekre et al. [144]	Embedded IoT monitoring system	Real-time solar PV data	GPRS	Fault detection and global data access	Yes
Adhya et al. [145]	Web-based IoT monitoring	PV plant performance data	Wi-Fi	Real-time monitoring, preventive maintenance, and fault detection	No
Emamian et al. [146]	Intelligent Monitoring System (IMS)	Voltage, current, temperature, humidity, irradiance	Wi-Fi	Fault detection, power prediction, and multi-user access	No
Shakya et al. [147]	IoT and data-mining techniques	Solar power generation	Wireless	Fault detection in large-scale solar plants	No
Suresh et al. [148]	IoT for solar fault prevention	Solar panel efficiency data	Wi-Fi	Preventive maintenance for enhanced efficiency	No
Del Río et al. [149]	IoT-based maintenance platform	SCADA data from solar plants	Wireless IoT communication	Pattern recognition for maintenance optimization	No
Kingsley et al. [150]	IoT-based fault monitoring	Output, temperature, voltage, frequency	Wi-Fi, GPRS	Real-time analysis and fault classification (98.95% accuracy)	No
Mellit et al. [151]	Internet-based solar monitoring	Air temp, sunlight, electrical output	Wireless	Real-time fault detection and notifications	Yes
Li et al. [152]	IoT-based system with TMS320F28335 DSP	PV array data (voltage, current, etc.), geographic and visual data	ZigBee	Real-time monitoring and fault diagnosis with 97.5% accuracy	No

Table 8. *Cont.*

Study	IoT Technology Used	Data Acquisition	Communication Protocol	Monitoring Features/Additional Functions	Low Cost
Xia et al. [153]	IoT-based real-time system with ZigBee	DC output, AC output, and power generation data	ZigBee for node communication, 4G for data transmission to cloud	Fault diagnosis, remote monitoring via web/mobile interface	Yes
Nalamwar et al. [154]	IoT solar panel management	Voltage, current, and generated electricity	Wireless	Automatic panel orientation adjustment	Yes
Hamied et al. [155]	Smart IoT-based remote sensing prototype	Voltage, current, and temperature	Wi-Fi	Effective remote monitoring and fault identification	Yes
Shirbhate and Barve [120]	Smart IoT solar system using Hidden Markov Model	Meteorological data	Wireless	Solar energy prediction using time series analysis	No
W Priharti et al. [156]	IoT-based solar PV monitoring	Voltage, current, temperature, irradiance	Wi-Fi	High accuracy (98.49%) in data capture; smartphone-based monitoring	No
Cheddadi et al. [157]	Open-source IoT solution	Environmental and solar power data	Wi-Fi	Real-time alerts for solar power deviations	Yes
Malik et al. [158]	IoT dust monitoring framework	Open-circuit voltage data	Wireless	Automatic cleaning trigger for solar panels	Yes
Narivos et al. [159]	IoT cleaning system for solar panels	Dust sensor, temperature, humidity	Wireless	Automated cleaning system triggered by dust accumulation	Yes
Ul Mehmood et al. [160]	Cloud-based Solar Conversion Recovery System (SCRS)	Light intensity, Temperature, Current, Voltage	MQTT	Optimized PV panel soiling monitoring (4.33% error rate)	Yes
Adila et al. [161]	Energy harvesting IoT network	Power harvesting from surroundings	Wireless	Ensures continuous power for low-powered devices over various distances	Yes

While these solar power monitoring systems provide real-time data for energy optimization and integration with IoT, issues such as sensor inaccuracies, integration limitations, and high initial costs restrict their wide-scale adoption, especially in smaller-scale setups. Most of the systems also lack user-friendly interfaces, robust data security, and mechanisms for effective fault prediction, hence the inefficiencies and downtime. Moreover, scalability is still an issue since upgrading a system to meet changing demands or regulations can be expensive, and technically intensive.

3.2.2. Optimization Techniques: MPPT, Solar Tracking, and Cleaning Systems

Despite the growth of global solar power generation capacity, the widespread adoption of PV systems remains limited due to high initial costs and the variability of energy output. Factors such as solar irradiance, ambient temperature, dust accumulation, and load conditions significantly impact PV performance. To address these challenges and ensure optimal operation under varying environmental conditions, a combination of Maximum Power Point Tracking (MPPT), solar tracking, and automated cleaning systems is essential.

The MPPT control system optimizes the performance of PV systems by dynamically adjusting their operating points to extract the maximum possible power. By continuously

monitoring and fine-tuning system settings, MPPT ensures that solar panels operate at their most efficient levels, enhancing energy generation and preventing underperformance [162].

Several studies focused on the design, performance, and optimization of single-axis solar tracking systems. In their paper, Rokonuzzaman et al. [163] present the design and implementation of an innovative MPPT solar charge controller (SCC) enhanced with IoT capabilities. The system incorporates IoT-based sensors to transmit critical data to the cloud, enabling remote monitoring and control. Utilizing the PIC16F877A microcontroller, it employs the perturb and observe (P&O) algorithm along with a customized buck–boost converter for efficient power management. Validation is performed through MATLAB/SIMULINK simulations and laboratory testing. The MPPT-SCC supports a maximum current of 10 A at 12 V, achieving an efficiency of up to 99.74% over a month-long testing period. Williams et al. [164] present the design and development of an IoT-based solar tracker with MPPT capabilities. The system predicts the sun's position to optimize power output, controls servos to adjust the solar panel's orientation, and monitors its performance. It collects and processes data, transmitting valuable insights to a remote station for further analysis. Similar trackers can be deployed in solar farms to enhance energy harvesting and management across large areas. By sending processed data to a centralized hub, these systems enable energy utility companies to optimize energy generation and consumption, improving overall efficiency. Similarly, Parveen et al. [165] aim to develop a highly precise solar tracker with MPPT and IoT-based data sharing. The tracking system operates in two stages: a primary stage using the sun–earth relationship for coarse adjustment and a secondary stage using Light-Dependent Resistor (LDR) sensors for fine-tuned azimuth and altitude adjustments. In cloudy or dusty conditions, the system relies solely on the primary stage to track the sun's position. By ensuring the solar panel remains perpendicular to sunlight, the tracker significantly enhances PV energy efficiency. Results demonstrate that the MPPT-enabled automatic tracking system is more reliable and efficient than a fixed solar panel. In their paper, Shah et al. [166] present the design of an IoT-based smart solar tracking system capable of panel rotation, cleaning, and performance monitoring. The system utilizes an Arduino Uno, a Wi-Fi module, and a mobile application for real-time data access and control. Both simulation and hardware analysis have been conducted to validate the system's effectiveness. The proposed design enhances solar panel efficiency by ensuring optimal positioning and maintenance through IoT integration. Also, Dandu et al. [167] present an IoT-integrated solar PV optimization system with MPPT that dynamically adjusts the position and orientation of a PV array in real time based on weather and solar irradiance data. The system comprises a microcontroller-based control unit, sensors for environmental monitoring, and a stepper motor to reposition the PV array for maximum energy capture. The control unit processes sensor data to determine the optimal positioning and directs the stepper motor accordingly. IoT connectivity enables remote monitoring and control, enhancing system efficiency. Simulation and experimental results confirm significant energy output improvements over fixed-position PV arrays. This cost-effective and efficient solution is suitable for both residential and commercial solar PV applications. Singh et al. [168] present an IoT-based solar tracking system designed to enhance solar panel efficiency by dynamically adjusting its orientation based on real-time weather and sunlight conditions. The system combines photoelectric detection and solar trajectory tracking, using sensors to assess weather conditions and determine the sun's position for precise tracking. Implemented with Arduino, NodeMCU, and environmental sensors, it enables remote monitoring and stable operation in various weather conditions. The proposed system significantly improves solar energy harvesting efficiency compared to fixed-mount panels. Moreover, Divakaran et al. [169] have developed a solar tracking system designed to capture maximum solar energy by following the sun's position.

The system rotates the solar panel setup along a single axis with one degree of freedom, driven by a DC motor controlled by an ATmega 2560 microcontroller. Light-Dependent Resistors are used to detect sunlight direction within a closed-loop system. This approach proved to be 71% more efficient than conventional fixed solar systems. The collected data are shared via IoT, enabling monitoring and control. Yaktu et al. [170] propose an IoT-based solar tracking system (STS) with MPPT that enhances solar energy harvesting efficiency by dynamically adjusting panel positions. A specialized hardware–software IoT-STS component enables real-time wireless communication between panels, ensuring optimal alignment. By integrating a backtracking strategy, the system minimizes shading effects and improves energy yield by up to 5% annually, especially in varying terrain conditions. The MPPT feature further optimizes power output, making the system highly efficient for solar energy generation. However, many focused on the development of double-axis solar tracking systems. Kumar et al. [171] present in their study an IoT-based two-axis solar tracking system (IoT-TASF) that integrates GPS, Artificial Neural Networks (ANNs), and image processing (IP) for precise sun tracking. The system optimizes panel orientation using real-time GPS and image data, while AI-driven decision-making adjusts for weather conditions. IoT enables remote monitoring and automation via cloud storage. Experimental results show a 59.21% power gain over fixed systems and reduced azimuth angle errors to 0.20 degrees, highlighting its efficiency and adaptability. Gbadamosi et al. [172] present the design and implementation of an IoT-based dual-axis solar PV tracking system. The proposed system integrates an Arduino-based microcontroller, GPS, web-based connectivity, and Light-Dependent Resistors (LDRs) to enhance solar tracking efficiency. The LDRs detect visible light intensity, guiding the movement of PV modules for optimal alignment with the sun. The tracking controller processes four intensity signals from the LDRs to adjust the panel's position based on the sun's daily trajectory. Experimental results demonstrate that the proposed system outperforms fixed solar panel setups in efficiency and energy capture. Also, in their project, Said et al. [173] focus on the development of a two-axis solar tracking system using an Arduino Uno as the main controller. The system employs four Light-Dependent Resistors to detect sunlight intensity and two servo motors to adjust the solar panel's position for optimal light absorption. A Wi-Fi ESP8266 module facilitates data transmission to an IoT-based monitoring system, which stores and displays performance data via a web platform. Efficiency tests comparing the two-axis tracker with a single-axis system show that the proposed system generates higher power, voltage, and current, demonstrating improved energy harvesting. Hammas et al. [174] recently presented a dual-axis tracking system that combines two tracking approaches: one using multiple LDR sensors managed by a PID controller for sunny conditions, and another using GPS and time-based control to calculate the sun's position (azimuth and altitude) on cloudy days. An IoT network is also established to monitor and support the system remotely. This smart setup results in a 33.23% increase in energy production compared to fixed systems, while minimizing unnecessary GPS usage. The prototype features two linear actuators for dual-axis movement and a 100W solar panel. Table 9 presents a comparison of the mentioned IoT-based solar tracking and MPPT systems, detailing the tracking type, whether MPPT is implemented, IoT functionalities, performance gains, and unique contributions of each study.

Table 9. Comparison of IoT-based solar tracking and MPPT systems.

Study	Tracking Type	MPPT Approach	IoT Functionalities	Performance Gains	Unique Contribution
Rokonuzzaman et al. [163]	MPPT solar charge controller	Yes	Cloud-based monitoring	99.74% efficiency	IoT-enhanced MPPT-SCC with buck–boost converter
Williams et al. [164]	Single-axis	Yes	Remote monitoring	Optimized energy harvesting	Predicts sun position for tracking in solar farms
Parveen et al. [165]	Single-axis Dual-stage tracking	Yes	IoT-based data sharing	Higher efficiency than fixed panels	Coarse sun–earth tracking + fine LDR adjustment
Shah et al. [166]	Single-axis	No	Mobile app control	Improved solar efficiency	IoT-enabled rotation, cleaning, and monitoring
Dandu et al. [167]	Adaptive tracking	Yes	Remote monitoring and control	Higher than fixed arrays	Dynamic adjustment based on real-time irradiance data
Singh et al. [168]	Single-axis	No	Remote monitoring	Higher energy capture than fixed panels	Combines photoelectric detection with environmental data
Divakaran et al. [169]	Single-axis	No	IoT monitoring and control	71% more efficient than fixed panels	ATmega 2560-controlled rotation
Yaktu et al. [170]	Adaptive tracking	Yes	IoT-STS component for wireless communication	5% annual energy gain	Backtracking strategy to minimize shading effects
Kumar et al. [171]	Two-axis	AI-based MPPT	Cloud automation	59.21% more power than fixed	Uses ANN, GPS, and image processing for tracking
Gbadamosi et al. [172]	Dual-axis	No	GPS and Web-based control	Higher than fixed panels	GPS and Arduino-based tracking using LDR sensors
Said et al. [173]	Two-axis	No	Web-based monitoring	Higher than single-axis tracking	Wi-Fi-based IoT system for monitoring
Hammas et al. [174]	Dual-axis	No	IoT network for monitoring and control	33.23% increase in energy production	Hybrid tracking using LDRs with PID for sunny days and GPS-based control for cloudy days

In the context of solar energy systems, maintaining optimal performance is paramount, and one significant challenge is the soiling of PV panels. Dust, dirt, and other particles that accumulate on PV panels can drastically reduce their efficiency and energy output. Research carried out in the United Arab Emirates [175] to assess the influence of dust on the performance of PV systems revealed that the PV power declined steadily by 1.7% per g/m^2 in both indoor and outdoor studies, with an accumulation of dust ranging from 5.44 g/m^2 over a period of 5 months; a 12.7% decrease in efficiency was detected as a result of soiling on the PV surfaces. Many projects focused on addressing this issue. In their research, Sulaiman et al. [176] show that the reduction in the peak power generated can be up to 18% in the performance of the solar PV panel. Rao et al. [177] observed that dust deposition significantly impacts the short-circuit current in PV systems, causing a reduction of 30–40% in indoor setups and 4–5% in outdoor test-beds, which results in significant power and economic losses for PV power plants, especially on a large scale. Additionally, a study by Rajput et al. [178] shows that dust considerably reduces the power production by 92.11% and efficiency as 89%. Kadir et al. [179] examined the impact of dust accumulation on solar panel efficiency by developing an IoT-based dust sensing system.

The system detected 30,411.53 mg/m³ of dust, and the solar panel's efficiency dropped from 15.42% to 0.74%. The efficiency reduction of approximately 15% was compared to similar studies, where efficiency losses due to dust accumulation ranged from 11.8% to 21.5%. Also, Suhaimi et al. [180] investigated the impact of dust on PV module performance and designed an IoT-based intelligent monitoring system to track the cleanliness of solar panels. The findings show that the output power drops below 4.85W (50% of its initial efficiency).

To minimize the negative effects of dust on PV panels, soiling monitoring and cleaning systems are essential. They detect and track dust accumulation on solar panels, enabling timely maintenance to optimize energy generation and reduce performance losses. To further address this issue, IoT-enabled cleaning systems have emerged, integrating sensors, real-time monitoring, and automated control mechanisms. These intelligent systems optimize cleaning schedules, conserve resources, and minimize human intervention by leveraging weather data, dirt accumulation metrics, and predictive maintenance algorithms. This combination ensures improved efficiency, reduced operational costs, and sustained solar panel performance.

Abdolzadeh and Ameri [181] developed a cleaning system with small holes positioned above the PV cells to spray water over them. This design increased the power output of the cells by 17% and improved PV cell efficiency to 3.26%. Although it is a very cost-effective, and efficient method for farmers even in hot weather, it is not suitable for arid regions. Moreover, manual labor is needed to remove sticky particles and for the maintenance of the pump. Also, a cost-effective water spray-based cleaning system was constructed to address the soiling effect on PV modules in the study [182] of Majeed et al. The system successfully restored 98% of the PV module efficiency and was considered suitable for commercial-scale applications. However, concerns were raised about the significant drop in efficiency when cleaning intervals were extended. A cleaning robot that uses a water sprayer and roller brush to remove dust from the panel surface was proposed by Jawale et al. [183]. An efficiency increase of 30–33% was observed; however, the need for external power sources adds to the system's overall cost. Meanwhile, the study by Parrott et al. [184] proposed a robotic system using a silicone rubber foam brush. Although it was found that a solar power plant cleaned every two weeks had an average performance loss of approximately 1.5% compared to daily cleaning with robotic technology, the system's effectiveness in removing sticky dirt, such as bird droppings, remains uncertain. Alagoz et al. [185] investigated the use of Surface Acoustic Wave (SAW) technology to clean solar PV panel surfaces. It achieved a 62% voltage rise, aiming to avoid the damage associated with abrasive mechanical cleaning methods. However, the technology proved less effective at removing dust particles smaller than 0.2 mm. On the other hand, Aly et al. [186] proposed a compressed air jet spraying system, capable of enhancing efficiency by up to 15%. Additionally, Mobin [187] developed a robotic cleaning system equipped with a waterproof pneumatic suction pump specifically for panel cleaning. However, its drawback lies in its inability to eliminate sticky dust. Memon, as well [188], proposed deploying autonomous vehicles for cleaning solar panels. However, it is expensive and does not have sufficient flexibility for quick movement. Table 10 presents a comparison of the mentioned cleaning methods, detailing the approach used, efficiency improvements achieved, and associated limitations.

MPPT techniques and solar tracking systems significantly enhance solar energy output by optimizing power extraction and panel orientation under varying environmental conditions. However, their effectiveness is contingent on precise algorithms, which can be computationally intensive and sensitive to hardware failures. Advanced MPPT methods, such as neural networks, are costly and require specialized expertise, making them less accessible to small-scale applications. Similarly, while solar tracking systems improve energy capture by aligning panels with the sun, their mechanical complexity raises installation

costs and maintenance challenges, particularly in harsh climates. Despite these advantages, both technologies require careful cost-benefit analysis and continuous innovation to remain economically viable.

Table 10. Comparison of solar panel cleaning methods.

Study	Method	Efficiency Gain	Limitations
Abdolzadeh and Ameri [181]	Water spray system	17% increase, 3.26% efficiency gain	Not suitable for arid regions, manual maintenance required
Majeed et al. [182]	Water spray system	98% efficiency restoration	Efficiency drops with extended cleaning intervals
Jawale et al. [183]	Water sprayer + roller brush robot	30–33% increase	Requires external power, higher cost
Parrott et al. [184]	Silicone rubber foam brush robot	1.5% loss with bi-weekly cleaning	Effectiveness on sticky dirt uncertain
Alagoz et al. [185]	Surface Acoustic Wave (SAW)	62% voltage rise	Ineffective for particles smaller than 0.2 mm
Aly et al. [186]	Compressed air jet system	15% efficiency gain	-
Mobin [187]	Robotic system with pneumatic suction	-	Cannot remove sticky dust
Memon [188]	Autonomous cleaning vehicle	-	Expensive, lacks quick movement flexibility

On the other hand, IoT-based cleaning systems offer significant benefits in optimizing solar energy systems: they allow for predictive maintenance and improving overall efficiency. However, their reliance on reliable connectivity makes them less effective in remote or poorly connected areas, limiting their applicability. Additionally, the high installation costs of IoT infrastructure—such as sensors, communication devices, and cloud services—can be prohibitive for smaller installations or markets in developing regions. Security and privacy concerns also pose risks, as the data collected from these systems are susceptible to cyberattacks, potentially leading to malfunctions or data breaches. Furthermore, the integration of IoT with legacy systems and the lack of standardization across platforms complicates seamless adoption.

3.3. Bridging AI and IoT: Innovations in PV Energy Management

The integration of AI and the IoT, collectively known as AIoT, is revolutionizing the way we manage and optimize PV systems. While IoT provides the necessary infrastructure to collect real-time data from solar panels and related components, AI enables the analysis and processing of these data to make intelligent decisions. Together, AI and IoT enable more efficient and automated energy management in PV systems. AIoT applications can optimize performance by predicting maintenance needs, improving energy storage, and enhancing system efficiency through real-time data analysis. This synergy not only maximizes energy production but also helps reduce operational costs, making AIoT a key enabler of smarter, more sustainable PV systems. In this section, we will examine some key contributions that bridge AI and IoT, emphasizing their synergistic role in optimizing PV system performance in real-world scenarios.

Starting with smart energy management systems, where Raju et al. [189] have developed a smart solar microgrid system that uses Arduino and IoT devices to collect real-time environmental data, like sunlight and temperature. The system is controlled by a Multi-

Agent System (MAS), which makes decisions on how to manage the energy, like whether to use it, store it, or share it. It is designed to handle the unpredictable nature of solar power and changing energy needs. The whole setup is tested using a simulation in JADE, and the decisions are shown using LED lights, making it easy to test and later apply in real situations. This collaborative approach led to more efficient demand-side management. Paradeep et al. [190] highlight in their work the integration of AI and the IoT in smart grid systems to enhance energy efficiency. IoT-enabled sensors collect real-time data on energy consumption, production, and environmental factors, allowing for the analysis of energy patterns and identification of inefficiencies. Using Bayesian optimization, a type of AI, the system can adaptively learn from historical data and real-time feedback to optimize energy consumption. This enables the smart grid to prioritize renewable energy sources, such as solar power, and dynamically adjust energy distribution. The combined use of IoT and AI improves grid performance, reduces energy waste, minimizes carbon emissions, and allows for proactive maintenance, making the grid more reliable and efficient. In South Korea, Joshua et al. [191] presented a real-world implementation of an AIoT-based solar–hydrogen energy management system at Kangwon National University's Samcheok Campus. The researchers aimed to enhance fault detection in solar panels by integrating deep learning models—MobileNetV2 and InceptionV3—into the system. These models were evaluated for their accuracy, loss values, and computational efficiency in detecting solar panel defects. MobileNetV2 achieved 80% accuracy and proved effective for resource-constrained environments, while InceptionV3 reached 90% accuracy with higher resource demands. By customizing ISO 50001:2018 standards [192] to the university's specific needs, the study underlines how AIoT and deep learning can be practically applied for sustainable and intelligent energy management in academic institutions. As well, Rojek et al. [193] present a real-world case study where solar energy is integrated into a distributed energy system using IoT and AI technologies. In this case study, IoT sensors and smart meters collect real-time data on energy usage, occupancy, temperature, and lighting, including solar energy generation. The AI algorithms then analyze these data to optimize solar energy generation, ensuring maximum efficiency. The case study highlights how solar energy is monitored and managed in a practical, real-world setting, demonstrating the feasibility, cost-effectiveness, and sustainability of using IoT and AI for energy management in buildings. In the context of agriculture, the paper by Ramli et al. [194] presents a solar-powered portable water pump (SPWP) integrated into an IoT-enabled smart irrigation system that was tested in a real-world environment. The system uses a NodeMCU microcontroller and sensors to monitor soil moisture, temperature, and humidity. It enables farmers to control the pump remotely through the Blynk IoT cloud and a smartphone app. The portable, eco-friendly pump is powered by solar energy and helps reduce electricity costs while improving water usage efficiency. The system's functionality and performance were practically evaluated, demonstrating its effectiveness in real-world agricultural settings. In smart home energy management, Rochd et al. [195] present the design and field implementation of a smart Home Energy Management System (HEMS) as part of a pilot project in a test-bed house at the Smart Campus in Benguerir, Morocco. The system improves residential energy efficiency through the smart integration and management of PV energy, using an AI-based multi-objective optimization algorithm. It combines supply-side (generation, storage, consumption) and demand-side (flexible appliance scheduling) management, based on electricity pricing, weather forecasts, PV generation, and user preferences. The results show that the system effectively reduces energy costs, boosts PV self-consumption, and balances comfort with savings, offering a promising model for scaling up smart energy solutions in residential buildings.

For fault detection in PV systems, the project by Cardinale et al. [196] demonstrates a real-world implementation of an AI-based IoT platform for diagnosing PV systems using infrared thermography (IRT). The system was tested on an actual PV installation, where various fault conditions—such as dirt, shading, and short-circuits—were intentionally induced to evaluate performance. Two AI models (deep learning and machine learning) were trained to detect hot spots under irradiance as low as 300 W/m^2, overcoming limitations of traditional IRT tools. The successful field deployment highlights the system's high sensitivity (0.995) and accuracy (0.923), offering a practical and cost-efficient tool for PV maintenance in real environments. An alternative perspective is offered by Menaka et al. [197]. In this paper, they review how AI and Industrial IoT (IIoT) can be integrated into solar energy systems at a national level. It highlights the use of solar-powered sensor nodes for monitoring and optimizing energy usage, fault detection in PV plants, and improving energy management. The proposed open-source, distributed architecture supports efficient solar energy harvesting and real-time data analysis. Overall, the study emphasizes how AI and IoT technologies can enhance the reliability, efficiency, and scalability of solar energy systems across national infrastructure. In a similar vein, Mostakim et al. [198] focus their article on the use of AI and IoT technologies to improve the efficiency of solar energy systems. It emphasizes the importance of smart solar panel cleaning systems that monitor and optimize panel performance by detecting dirt and debris, which reduce energy production. The study compares traditional cleaning methods to autonomous smart systems, which provide real-time purification and remote monitoring. A pilot project demonstrated the effectiveness of these smart systems in increasing solar power generation and reducing operational costs. The article also explores the role of AI (including machine learning and deep learning) and IoT in enhancing energy distribution, renewable energy generation, and grid management. The integration of these technologies is shown to improve energy efficiency, reduce costs, and increase the resilience of electrical systems.

In the field of solar powered electric vehicles, Raza et al. [199] discuss solutions for charging systems using hybrid sources, particularly solar energy, alongside plug-in hybrid electric vehicles (PHEVs) and all-electric vehicles (EVs). It emphasizes the role of solar power in hybrid charging systems, where solar panels directly charge the vehicle's battery, which is then used to power the vehicle. As the vehicle operates, the battery is charged through multiple sources, including solar energy. They explore how the IoT and AI can enhance the monitoring of charging systems and enable fully autonomous driving in EVs through connected sensors. AI automates decision-making and tasks, advancing the move toward full automation for electric vehicles. In the future, solar-powered, IoT, and AI-based autonomous EVs could help reduce battery charging times, parking issues, and traffic problems, while promoting the development of smart cities.

The integration of Artificial Intelligence (AI) and the IoT in photovoltaic PV energy systems marks a significant step toward smarter and more efficient energy management. By enabling real-time monitoring, fault detection, and predictive analytics, AIoT enhances the performance and reliability of PV installations. This synergy supports data-driven decisions, optimizes energy output, and contributes to sustainability goals. However, challenges remain—such as high setup costs, data security risks, device interoperability, and the demand for advanced computational resources. These barriers highlight the need for scalable, secure, and user-friendly AIoT solutions to fully unlock their potential in PV energy applications.

4. Discussion

The integration of AIoT in solar energy monitoring and control has markedly improved the efficiency, reliability, and automation of PV systems. Despite these advance-

ments, several critical challenges remain, limiting widespread adoption and optimal system performance. Overcoming these barriers is crucial to developing more resilient, adaptive, and intelligent solar infrastructures. Future research must prioritize the advancement of robust and efficient AI algorithms, the incorporation of emerging technologies, and the development of standardized frameworks that support interoperability, scalability, and long-term sustainability.

This section highlights the key challenges currently facing AIoT-based solar energy systems and outlines promising research directions poised to shape the evolution of the next generation of intelligent, scalable, and resilient AIoT-powered PV systems.

4.1. Challenges

4.1.1. Data-Related Challenges

The effectiveness of AIoT applications in solar energy systems is fundamentally dependent on the availability of high-quality, diverse, and real-time datasets for training, validating, and refining AI models. However, ensuring consistent and accurate data collection remains a major obstacle. Environmental variability, sensor degradation, and intermittent or incomplete data streams frequently compromise data reliability. The integration of heterogeneous data sources—ranging from meteorological information and PV performance metrics to IoT sensor outputs—adds complexity, necessitating sophisticated data preprocessing, cleaning, and fusion techniques to ensure consistency and usability. Moreover, data privacy and security are critical concerns, particularly when sensitive operational data are transmitted over cloud-based platforms. This risk is amplified in regions lacking robust cybersecurity infrastructure, increasing vulnerability to data breaches or unauthorized access. These challenges must be addressed to establish trustworthy, scalable, and resilient AIoT frameworks capable of supporting real-time monitoring, predictive analytics, and adaptive control in solar energy systems.

4.1.2. Model-Specific Challenges

Developing robust AI models for PV system monitoring and fault detection involves several key challenges related to accuracy, adaptability, and computational efficiency. While many models demonstrate strong performance in controlled environments, they often falter when exposed to real-world variability—such as fluctuating weather conditions, sensor noise, and unanticipated fault scenarios. A common limitation is overfitting, where models are overly tailored to training data and fail to generalize across diverse PV installations. Computational demands pose another barrier, particularly for deep learning architectures. These models often require significant processing power, making them unsuitable for deployment on resource-constrained edge devices where low latency and energy efficiency are critical. Balancing model complexity with lightweight, real-time performance is essential for effective fault detection and system responsiveness. Additionally, a lack of transparency in many AI models—especially deep learning approaches—undermines operator trust. Without explainable outputs, it becomes difficult to interpret predictions, verify results, or justify automated decisions. Overcoming these limitations calls for the development of adaptable, energy-efficient AI architectures that maintain high accuracy in diverse operational contexts. Incorporating explainable AI (XAI) techniques will also be key to building user trust and facilitating broader adoption in solar energy applications.

4.1.3. Field-Level and Deployment Challenges

Deploying AIoT-based solar energy monitoring and control systems in real-world environments involves numerous field-level and infrastructural challenges. One critical issue is communication stability, especially in remote or decentralized solar farms where intermittent network coverage can lead to delays or data loss during real-time transmission and

control. Sensor accuracy and reliability also pose significant challenges—malfunctioning or miscalibrated sensors can provide erroneous input to AI models, compromising system performance and decision-making. In addition to these field-level concerns, computational limitations remain a barrier. Many AI models require high processing power, making deployment on resource-constrained edge devices difficult. Integration with existing PV infrastructure is often complicated by heterogeneity in hardware standards, communication protocols, and control systems, leading to compatibility issues. Real-time responsiveness is another key concern, particularly under fluctuating solar irradiance, unpredictable load demands, or actuator latency. Ensuring reliable and adaptive system behavior under these dynamic conditions requires robust AI algorithms and control strategies. Furthermore, cybersecurity threats become more prominent as these systems rely heavily on distributed and cloud-based architectures. Unauthorized access or data breaches can lead to serious disruptions in operations. Lastly, economic factors, including the cost of hardware, AI integration, and maintenance, can hinder widespread adoption, particularly in small-scale or underfunded solar projects. To address these challenges, future research should focus on developing lightweight and energy-efficient AI models, improving communication resilience, enhancing sensor calibration and diagnostics, and promoting standardized frameworks that support seamless integration and scalability in diverse PV environments.

4.1.4. Environmental and Sensor Limitations

AIoT-based solar energy monitoring and control systems depend heavily on sensor data for intelligent decision-making, yet environmental conditions and sensor limitations pose persistent challenges. Harsh weather—such as extreme temperatures, dust, humidity, and heavy rainfall—can impair sensor performance, resulting in inaccurate data and unreliable AI predictions. Fluctuations in solar irradiance due to cloud cover or shading further complicate real-time forecasting and energy optimization. Over time, sensor drift, calibration errors, and aging degrade measurement accuracy, necessitating regular maintenance and recalibration, which adds to operational costs. Sensor placement and quality are also critical, as poor positioning can lead to data inconsistencies that undermine AI-driven control strategies. Additionally, power limitations in wireless IoT sensors introduce trade-offs between sampling frequency and battery life, constraining real-time monitoring. To overcome these issues, future systems must adopt self-calibrating sensors, robust signal processing to handle noise and missing data, and energy-efficient sensing protocols. These advancements will improve the reliability, accuracy, and resilience of AIoT-based solar energy solutions.

4.2. Future Aspects

4.2.1. Advancements in AI Algorithms

Future AIoT-based solar energy systems will increasingly leverage advanced AI techniques to boost accuracy, adaptability, and real-time decision-making. Hybrid AI models that combine deep learning, fuzzy logic, and evolutionary algorithms will enhance fault detection, energy forecasting, and system optimization under dynamic and uncertain conditions. GenAI is set to transform PV monitoring and diagnostics by improving anomaly detection, automating fault classification, and generating predictive insights. Its ability to model complex patterns enables early detection of system degradation, more accurate maintenance scheduling, and reduced false positives in fault alerts. Explainable AI (XAI) will be essential for building trust and transparency, allowing operators to interpret and validate AI-generated insights. Reinforcement learning and self-optimizing models will support adaptive control by continuously tuning parameters such as panel orientation, battery usage, and grid interactions based on real-time feedback. Furthermore, the adoption

of physics-informed AI—combining domain knowledge with data-driven methods—will improve model generalization and reliability, especially in data-scarce environments. Collectively, these innovations mark a shift toward intelligent, autonomous, and resilient energy management in next-generation solar systems.

4.2.2. Integration of Emerging Technologies

The future of AIoT-powered solar energy systems will be shaped by the convergence of emerging technologies such as Edge AI, Federated Learning, Blockchain, Digital Twins, and 6G networks—enabling smarter, more secure, and efficient energy management. Edge AI will minimize reliance on cloud infrastructure by processing data locally on IoT devices, reducing latency and energy use while enabling real-time decision-making. Federated Learning will address privacy concerns by training AI models across distributed solar installations without sharing raw data, enhancing both security and model accuracy. Blockchain will play a critical role in securing energy transactions, supporting transparent peer-to-peer trading, and enabling decentralized grid operations. Digital Twins—virtual replicas of PV systems—will allow operators to simulate performance, predict failures, and test control strategies without physical risks. The rollout of 6G networks will further enhance device connectivity, delivering ultra-fast data transfer, improved synchronization across distributed systems, and more reliable AI-based automation. Together, these technologies will drive the next generation of AIoT-enabled solar systems, making them more autonomous, scalable, and resilient to both environmental and operational challenges.

4.2.3. Enhanced Data Analytics

Future AIoT-driven solar energy systems will harness advanced data analytics to enhance decision-making, optimize energy output, and enable predictive maintenance. Intelligent analytics, including self-learning algorithms and real-time anomaly detection, will allow PV systems to identify inefficiencies, detect faults, and adapt dynamically to environmental changes. Big data techniques will integrate vast streams of structured and unstructured data—from IoT sensors, weather forecasts, and grid interactions—boosting the accuracy of energy forecasting. GenAI will play a key role by generating synthetic datasets, simulating complex operational scenarios, and improving fault prediction in data-scarce settings. Automated feature selection and dimensionality reduction methods, such as VAEs and PCA, will streamline data pipelines, enhancing model efficiency and scalability. Moreover, cloud–edge hybrid analytics will distribute workloads efficiently, with edge devices handling time-sensitive data and cloud infrastructure performing deeper, long-term analysis. Together, these advancements will drive more proactive, adaptive, and intelligent AIoT-based solar energy management.

4.2.4. Standardization and Collaboration

The widespread adoption of AIoT in solar energy systems will require coordinated global efforts to establish standardized protocols, interoperability frameworks, and collaborative research initiatives. Currently, the absence of uniform data formats, communication protocols, and integration standards across various AIoT platforms creates challenges for seamless deployment and scalability. Developing global interoperability standards for AI and IoT will ensure compatibility among diverse PV systems, sensors, and grid infrastructures, thus fostering a more unified energy ecosystem. Collaboration among academia, industry, and policymakers will be crucial to driving innovation, enhancing cybersecurity, and ensuring regulatory compliance for AI-driven solar energy management. Open-source initiatives and shared datasets can significantly accelerate research, allowing AI models to be trained on diverse and representative data. Furthermore, cross-sector partnerships—including energy providers, AI researchers, and IoT manufacturers—will facilitate the creation of more efficient,

transparent, and secure AIoT-based solar energy solutions. By prioritizing standardization and fostering collaboration, the industry can overcome existing challenges, ensuring a more sustainable and globally integrated future for AI-powered solar energy systems.

5. Conclusions

The integration of AIoT in PV systems represents a game-changing approach to enhancing solar energy monitoring, fault detection, and optimization. This survey explores the core applications of AI and IoT in solar energy systems, highlighting their roles in improving efficiency, reliability, and sustainability. By utilizing AI techniques such as ML, DL, and GenAI, solar energy systems can achieve advanced fault diagnosis, predictive maintenance, and accurate energy forecasting. Meanwhile, IoT-enabled solutions enable real-time monitoring, smart tracking, and automated cleaning, ensuring peak system performance.

Despite these advancements, several challenges remain, including issues related to data, model adaptability, deployment constraints, and environmental limitations. Overcoming these challenges will require further research into scalable AI models, resilient IoT architectures, and advanced data-processing techniques. Additionally, emerging technologies like Edge AI, Federated Learning, Blockchain, and Digital Twins hold significant promise for shaping the future of AIoT-driven solar systems. Standardization and cross-sector collaboration will be crucial to addressing interoperability barriers and accelerating the global adoption of AIoT solutions.

Looking ahead, the continuous evolution of AIoT will pave the way for more intelligent, autonomous, and efficient solar energy management systems. By integrating advanced analytics, real-time optimization, and secure data-sharing mechanisms, AIoT has the potential to usher in a new era of sustainable energy solutions. This survey lays the groundwork for future research and innovation, offering valuable insights into the current landscape and future possibilities of AIoT in solar energy applications.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AIoT	Artificial Internet of Things
ANN	Artificial Neural Network
ANNBM	Artificial Neural Network-Based Model
ART	Adaptive Resonance Theory
CNN	Convolutional Neural Network
DA-DCGAN	Domain Adaptation and Deep Convolutional Generative Adversarial Network
DNN	Deep Neural Network
DT	Decision Tree
ETSG	Electrical Time Series Graph
FCM	Fuzzy C-Mean
FFBP	Feedforward Backpropagation
FFNN	Feedforward Neural Network

GANs	Generative Adversarial Networks
GLQA	Grey Scale Quantization algorithm
GRNN	Generalized Regression Neural Network
GPR	Gaussian Process Regression
HE	Histogram Equalization
IoT	Internet of Things
IR	Infrared
KNN	k-Nearest Neighbors
LSTM	Long Short-Term Memory
MLP	Multilayer Perceptron
MOPSO	Multi-Objective Particle Swarm Optimization
MPPT	Maximum Power Point Tracking
nRMSE	normalized Root Mean Square Error
PLC	Programmable Logic Controllers
PNN	Probabilistic Neural Network
PV	Photovoltaic
RBFNN	Radial Basis Function Neural Network
ResNet	Residual Network
RF	Random Forest
RHA	Region-Based Histogram Approach
RNNs	Recurrent Neural Networks
SCADA	Supervisory Control and Data Acquisition
SOM	Self-Organizing Map
SVM	Support Vector Machine
TMA	Triangular Moving Average
UAV	Unmanned Aerial Vehicle
VAE	Variational Autoencoder

References

1. Marks-Bielska, R.; Bielski, S.; Pik, K.; Kurowska, K. The importance of renewable energy sources in Poland's energy mix. *Energies* **2020**, *13*, 4624. [CrossRef]
2. Siddique, H.M.A.; Kiani, A.K. Industrial pollution and human health: Evidence from middle-income countries. *Environ. Sci. Pollut. Res.* **2020**, *27*, 12439–12448. [CrossRef]
3. Martins, F.; Felgueiras, C.; Smitkova, M.; Caetano, N. Analysis of fossil fuel energy consumption and environmental impacts in European countries. *Energies* **2019**, *12*, 964. [CrossRef]
4. Qiu, T.; Wang, L.; Lu, Y.; Zhang, M.; Qin, W.; Wang, S.; Wang, L. Potential assessment of photovoltaic power generation in China. *Renew. Sustain. Energy Rev.* **2022**, *154*, 111900. [CrossRef]
5. Casey, J. World Adds 553GW of Solar Capacity in 2024 as Energy Demand Grows. 2025. Available online: https://www.pv-tech.org/world-adds-553gw-solar-capacity-2024-energy-demand-grows/ (accessed on 10 April 2025).
6. Casey, J. Ember: Global Solar Generation Exceeds 2,000TWh in 2024. 2025. Available online: https://www.pv-tech.org/ember-global-solar-generation-exceeds-2000twh-2024/ (accessed on 10 April 2025).
7. Sahu, D.K.; Brahmin, A. A review on solar monitoring system. *Int. Res. J. Eng. Technol.* **2021**, *8*, 111–113.
8. Merza, B.N.; Wadday, A.G.; Abdullah, A.K. Study and analysis of fault detection in solar array system based on internet of things. *AIP Conf. Proc.* **2024**, *3092*, 050010.
9. Kalogirou, S.A. Artificial neural networks in renewable energy systems applications: A review. *Renew. Sustain. Energy Rev.* **2001**, *5*, 373–401. [CrossRef]
10. Mellit, A.; Kalogirou, S.A. Artificial intelligence techniques for photovoltaic applications: A review. *Prog. Energy Combust. Sci.* **2008**, *34*, 574–632. [CrossRef]
11. Mellit, A.; Kalogirou, S.A.; Hontoria, L.; Shaari, S. Artificial intelligence techniques for sizing photovoltaic systems: A review. *Renew. Sustain. Energy Rev.* **2009**, *13*, 406–419. [CrossRef]
12. Zhao, H.x.; Magoulès, F. A review on the prediction of building energy consumption. *Renew. Sustain. Energy Rev.* **2012**, *16*, 3586–3592. [CrossRef]
13. Dounis, A.I.; Caraiscos, C. Advanced control systems engineering for energy and comfort management in a building environment—A review. *Renew. Sustain. Energy Rev.* **2009**, *13*, 1246–1261. [CrossRef]

14. Russell, S.J.; Norvig, P. *Artificial Intelligence: A Modern Approach*; Pearson: London, UK, 2016.
15. Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; Bengio, Y. Generative adversarial networks. *Commun. ACM* **2020**, *63*, 139–144. [CrossRef]
16. Mellit, A.; Kalogirou, S. Artificial intelligence and internet of things to improve efficacy of diagnosis and remote sensing of solar photovoltaic systems: Challenges, recommendations and future directions. *Renew. Sustain. Energy Rev.* **2021**, *143*, 110889. [CrossRef]
17. Mitchell, T.M.; Mitchell, T.M. *Machine Learning*; McGraw-Hill New York: New York, NY, USA, 1997; Volume 1.
18. Zhu, X.J. *Semi-Supervised Learning Literature Survey*; University of Wisconsin-Madison Department of Computer Sciences: Madison, WI, USA, 2005.
19. Hastie, T. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*; Springer: New York, NY, USA, 2009.
20. Sutton, R.S.; Barto, A.G. *Reinforcement Learning: An Introduction*; MIT Press: Cambridge, MA, USA, 2018.
21. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef]
22. Goodfellow, I. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016.
23. Hochreiter, S. Long Short-term Memory. *Neural Comput.* **1997**, *9*, 1735–1780. [CrossRef]
24. Rumelhart, D.E.; Hinton, G.E.; Williams, R.J. Learning representations by back-propagating errors. *Nature* **1986**, *323*, 533–536. [CrossRef]
25. Deng, L.; Yu, D. Deep learning: Methods and applications. *Found. Trends Signal Process.* **2014**, *7*, 197–387. [CrossRef]
26. Bandi, A.; Adapa, P.V.S.R.; Kuchi, Y.E.V.P.K. The power of generative ai: A review of requirements, models, input–output formats, evaluation metrics, and challenges. *Future Internet* **2023**, *15*, 260. [CrossRef]
27. Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; Bengio, Y. Generative adversarial nets. In *Advances in Neural Information Processing Systems 27 (NeurIPS 2014)*; Curran Associates, Inc.: Red Hook, NY, USA, 2014.
28. Kingma, D.P. Auto-encoding variational bayes. *arXiv* **2013**, arXiv:1312.6114.
29. Vaswani, A. Attention is all you need. In *Advances in Neural Information Processing Systems 30 (NeurIPS 2017)*; Curran Associates, Inc.: Red Hook, NY, USA, 2017.
30. Sohl-Dickstein, J.; Weiss, E.; Maheswaranathan, N.; Ganguli, S. Deep Unsupervised Learning Using Nonequilibrium Thermodynamics. In Proceedings of the 32nd International Conference on Machine Learning (ICML 2015), Lille, France, 7–9 July 2015; PMLR: Brookline, MA, USA, 2015; pp. 2256–2265.
31. Haseeb, K.; Almogren, A.; Islam, N.; Ud Din, I.; Jan, Z. An energy-efficient and secure routing protocol for intrusion avoidance in IoT-based WSN. *Energies* **2019**, *12*, 4174. [CrossRef]
32. Ramamurthy, A.; Jain, P. *The Internet of Things in the Power Sector Opportunities in Asia and the Pacific*; Asian Development Bank: Manila, Philippines, 2017. Available online: https://pdfs.semanticscholar.org/77dc/e7550d729f5a4ab871d9f868c0c5acc93234.pdf (accessed on 15 October 2024).
33. Kelly, S.D.T.; Suryadevara, N.K.; Mukhopadhyay, S.C. Towards the implementation of IoT for environmental condition monitoring in homes. *IEEE Sensors J.* **2013**, *13*, 3846–3853. [CrossRef]
34. Element, N. Smart Sensor Technology for the IoT. *Tech Briefs*, 2018. Available online: https://www.techbriefs.com/component/content/article/33212-smart-sensor-technology-for-the-iot (accessed on 19 November 2024).
35. Co, I. 8 Types of Sensors that Coalesce Perfectly with an IoT App. 2018. Available online: https://www.itfirms.co/8-types-of-sensors-that-coalesce-perfectly-with-an-iot-app/ (accessed on 15 October 2024).
36. Morris, A.; Langari, R. Level Measurement. In *Measurement and Instrumentation*, 2nd ed.; Morris, A., Langari, R., Eds.; Academic Press: Boston, MA, USA, 2016; Chapter 17, pp. 531–545.
37. Motlagh, N.H.; Khajavi, S.H.; Jaribion, A.; Holmstrom, J. An IoT-based automation system for older homes: A use case for lighting system. In Proceedings of the 2018 IEEE 11th Conference on Service-Oriented Computing and Applications (SOCA), Paris, France, 20–22 November 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
38. Pérez-Lombard, L.; Ortiz, J.; Pout, C. A review on buildings energy consumption information. *Energy Build.* **2008**, *40*, 394–398. [CrossRef]
39. Bose, I.; Sengupta, S.; Ghosh, S.; Saha, H.; Sengupta, S. Development of smart dust detector for optimal generation of SPV power plant by cleaning initiation. *Sol. Energy* **2024**, *276*, 112643. [CrossRef]
40. Kececi, E. Actuators. In *Mechatronic Components*; Kececi, E., Ed.; Butterworth-Heinemann: Oxford, UK, 2019; Chapter 11, pp. 145–154.
41. Eugenio, C. Manufacturing Low-Cost WiFi-Based Electric Energy Meter. In Proceedings of the 2014 IEEE Central America and Panama Convention (CONCAPAN XXXIV), Panama City, Panama, 12–14 November 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 1–6.
42. Lee, Y.T.; Hsiao, W.H.; Huang, C.M.; Seng-cho, T.C. An integrated cloud-based smart home management system with community hierarchy. *IEEE Trans. Consum. Electron.* **2016**, *62*, 1–9. [CrossRef]

43. Lee, J.S.; Su, Y.W.; Shen, C.C. A Comparative Study of Wireless Protocols: Bluetooth, UWB, ZigBee, and Wi-Fi. In Proceedings of the IECON 2007—33rd Annual Conference of the IEEE Industrial Electronics Society, Taipei, Taiwan, 5–8 November 2007; IEEE: Piscataway, NJ, USA, 2007; pp. 46–51.
44. Collotta, M.; Pau, G. A solution based on bluetooth low energy for smart home energy management. *Energies* **2015**, *8*, 11916–11938. [CrossRef]
45. Craig, W.C. *Zigbee: Wireless Control That Simply Works*; Zigbee Alliance: San Ramon, CA, USA, 2004.
46. Batista, N.; Melício, R.; Matias, J.; Catalão, J. Photovoltaic and wind energy systems monitoring and building/home energy management using ZigBee devices within a smart grid. *Energy* **2013**, *49*, 306–315. [CrossRef]
47. Augustin, A.; Yi, J.; Clausen, T.; Townsley, W.M. A study of LoRa: Long range & low power networks for the internet of things. *Sensors* **2016**, *16*, 1466. [CrossRef] [PubMed]
48. Ferreira, J.C.; Afonso, J.A.; Monteiro, V.; Afonso, J.L. An energy management platform for public buildings. *Electronics* **2018**, *7*, 294. [CrossRef]
49. Wei, J.; Han, J.; Cao, S. Satellite IoT edge intelligent computing: A research on architecture. *Electronics* **2019**, *8*, 1247. [CrossRef]
50. De Sanctis, M.; Cianca, E.; Araniti, G.; Bisio, I.; Prasad, R. Satellite communications supporting internet of remote things. *IEEE Internet Things J.* **2015**, *3*, 113–123. [CrossRef]
51. Walz, A.; Niemann, K.H.; Göppert, J.; Fischer, K.; Merklin, S.; Ziegler, D.; Sikora, A. Profinet Security: A Look on Selected Concepts for Secure Communication in the Automation Domain. In Proceedings of the 2023 IEEE 21st International Conference on Industrial Informatics (INDIN), Lemgo, Germany, 17–20 July 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–6.
52. Găitan, V.G.; Zagan, I. Modbus protocol performance analysis in a variable configuration of the physical fieldbus architecture. *IEEE Access* **2022**, *10*, 123942–123955. [CrossRef]
53. Hsiao, C.H.; Lee, W.P. OPIIoT: Design and implementation of an open communication protocol platform for industrial internet of things. *Internet Things* **2021**, *16*, 100441. [CrossRef]
54. Silva, M.; Pereira, F.; Soares, F.; Leão, C.P.; Machado, J.; Carvalho, V. An Overview of Industrial Communication Networks. In *New Trends in Mechanism and Machine Science: From Fundamentals to Industrial Applications*; Springer: Cham, Switzerland, 2015; pp. 933–940.
55. Lakshminarayana, S.; Praseed, A.; Thilagam, P.S. Securing the IoT application layer from an MQTT protocol perspective: Challenges and research prospects. *IEEE Commun. Surv. Tutor.* **2024**, *26*, 2510–2546. [CrossRef]
56. Jaribion, A.; Khajavi, S.H.; Motlagh, N.H.; Holmström, J. [WiP] A Novel Method for Big Data Analytics and Summarization Based on Fuzzy Similarity Measure. In Proceedings of the 2018 IEEE 11th Conference on Service-Oriented Computing and Applications (SOCA), Paris, France, 20–22 November 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 221–226.
57. Chen, M.; Mao, S.; Liu, Y. Big data: A survey. *Mob. Networks Appl.* **2014**, *19*, 171–209. [CrossRef]
58. Stojmenovic, I. Machine-to-machine communications with in-network data aggregation, processing, and actuation for large-scale cyber-physical systems. *IEEE Internet Things J.* **2014**, *1*, 122–128. [CrossRef]
59. Shi, W.; Cao, J.; Zhang, Q.; Li, Y.; Xu, L. Edge computing: Vision and challenges. *IEEE Internet Things J.* **2016**, *3*, 637–646. [CrossRef]
60. Satyanarayanan, M. The emergence of edge computing. *Computer* **2017**, *50*, 30–39. [CrossRef]
61. Stergiou, C.; Psannis, K.E.; Kim, B.G.; Gupta, B. Secure integration of IoT and cloud computing. *Future Gener. Comput. Syst.* **2018**, *78*, 964–975. [CrossRef]
62. Ji, C.; Li, Y.; Qiu, W.; Awada, U.; Li, K. Big Data Processing in Cloud Computing Environments. In Proceedings of the 2012 12th International Symposium on Pervasive Systems, Algorithms and Networks, San Marcos, TX, USA, 13–15 December 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 17–23.
63. Foster, I.; Zhao, Y.; Raicu, I.; Lu, S. Cloud Computing and Grid Computing 360-Degree Compared. In Proceedings of the 2008 Grid Computing Environments Workshop, Austin, TX, USA, 12–16 November 2008; IEEE: Piscataway, NJ, USA, 2008; pp. 1–10.
64. Hamdaqa, M.; Tahvildari, L. Cloud computing uncovered: A research landscape. *Adv. Comput.* **2012**, *86*, 41–85.
65. Khan, Z.; Anjum, A.; Kiani, S.L. Cloud Based Big Data Analytics for Smart Future Cities. In Proceedings of the 2013 IEEE/ACM 6th International Conference on Utility and Cloud Computing (UCC), Dresden, Germany, 9–12 December 2013; IEEE: Piscataway, NJ, USA, 2013; pp. 381–386.
66. Mahmud, R.; Kotagiri, R.; Buyya, R. Fog computing: A taxonomy, survey and future directions. In *Internet of Everything: Algorithms, Methodologies, Technologies and Perspectives*; Springer: Singapore, 2018; pp. 103–130.
67. Verma, M.; Bhardwaj, N.; Yadav, A.K. Real time efficient scheduling algorithm for load balancing in fog computing environment. *Int. J. Inf. Technol. Comput. Sci.* **2016**, *8*, 1–10. [CrossRef]
68. Atlam, H.F.; Walters, R.J.; Wills, G.B. Fog computing and the internet of things: A review. *Big Data Cogn. Comput.* **2018**, *2*, 10. [CrossRef]
69. Venkatesh, S.N.; Jeyavadhanam, B.R.; Sizkouhi, A.M.; Esmailifar, S.M.; Aghaei, M.; Sugumaran, V. Automatic detection of visual faults on photovoltaic modules using deep ensemble learning network. *Energy Rep.* **2022**, *8*, 14382–14395. [CrossRef]

70. Prabhakaran, S.; Uthra, R.A.; Preetharoselyn, J. Deep Learning-Based Model for Defect Detection and Localization on Photovoltaic Panels. *Comput. Syst. Sci. Eng.* **2023**, *44*, 2683–2700. [CrossRef]
71. Singh, O.D.; Gupta, S.; Dora, S. Segmentation technique for the detection of Micro cracks in solar cell using support vector machine. *Multimed. Tools Appl.* **2023**, *82*, 32091–32116. [CrossRef]
72. Wang, Y.; Shen, L.; Li, M.; Sun, Q.; Li, X. PV-YOLO: Lightweight YOLO for photovoltaic panel fault detection. *IEEE Access* **2023**, *11*, 10966–10976.
73. Huang, J.; Zeng, K.; Zhang, Z.; Zhong, W. Solar panel defect detection design based on YOLO v5 algorithm. *Heliyon* **2023**, *9*, e18826. [CrossRef]
74. Özer, T.; Türkmen, Ö. Low-cost AI-based solar panel detection drone design and implementation for solar power systems. *Robot. Intell. Autom.* **2023**, *43*, 605–624. [CrossRef]
75. Özer, T.; Türkmen, Ö. An approach based on deep learning methods to detect the condition of solar panels in solar power plants. *Comput. Electr. Eng.* **2024**, *116*, 109143. [CrossRef]
76. Jiang, L.L.; Maskell, D.L. Automatic fault detection and diagnosis for photovoltaic systems using combined artificial neural network and analytical based methods. In Proceedings of the 2015 International Joint Conference on Neural Networks (IJCNN), Killarney, Ireland, 12–17 July 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 1–8.
77. Abdallah, F.S.M.; Abdullah, M.; Musirin, I.; Elshamy, A.M. Intelligent solar panel monitoring system and shading detection using artificial neural networks. *Energy Rep.* **2023**, *9*, 324–334. [CrossRef]
78. Benkercha, R.; Moulahoum, S. Fault detection and diagnosis based on C4. 5 decision tree algorithm for grid connected PV system. *Sol. Energy* **2018**, *173*, 610–634. [CrossRef]
79. Harrou, F.; Taghezouit, B.; Sun, Y. Improved *k* NN-based monitoring schemes for detecting faults in PV systems. *IEEE J. Photovoltaics* **2019**, *9*, 811–821. [CrossRef]
80. Hossain, S.; Arika, A.M.; Fahim, I.N.; Uddin, J.; Ahmed, A.; Apon, H.J.; Hoque, M.A. Enhancing solar panel performance: A machine learning approach to dust detection and automated water sprinkle-based cleaning strategy. *Sol. Energy* **2025**, *287*, 113240. [CrossRef]
81. Mekki, H.; Mellit, A.; Salhi, H.; Guessoum, A. Artificial neural Network-Based modeling and monitoring of photovoltaic generator. *MJMS* **2015**, *3*, 9.
82. Karatepe, E.; Hiyama, T. Controlling of artificial neural network for fault diagnosis of photovoltaic array. In Proceedings of the 2011 16th International Conference on Intelligent System Applications to Power Systems, Hersonissos, Greece, 25–28 September 2011; IEEE: Piscataway, NJ, USA, 2011; pp. 1–6.
83. Lu, S.; Sirojan, T.; Phung, B.T.; Zhang, D.; Ambikairajah, E. DA-DCGAN: An effective methodology for DC series arc fault diagnosis in photovoltaic systems. *IEEE Access* **2019**, *7*, 45831–45840. [CrossRef]
84. Chao, K.H.; Chen, C.T.; Wang, M.H.; Wu, C.F. A novel fault diagnosis method based-on modified neural networks for photovoltaic systems. In Proceedings of the Advances in Swarm Intelligence: First International Conference, ICSI 2010, Beijing, China, 12–15 June 2010; Proceedings, Part II 1; Springer: Berlin/Heidelberg, Germany, 2010; pp. 531–539.
85. Akram, M.N.; Lotfifard, S. Modeling and health monitoring of DC side of photovoltaic array. *IEEE Trans. Sustain. Energy* **2015**, *6*, 1245–1253. [CrossRef]
86. Zhao, Y.; Yang, L.; Lehman, B.; de Palma, J.F.; Mosesian, J.; Lyons, R. Decision tree-based fault detection and classification in solar photovoltaic arrays. In Proceedings of the 2012 Twenty-Seventh Annual IEEE Applied Power Electronics Conference and Exposition (APEC), Orlando, FL, USA, 5–9 February 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 93–99.
87. Chen, Z.; Han, F.; Wu, L.; Yu, J.; Cheng, S.; Lin, P.; Chen, H. Random forest based intelligent fault diagnosis for PV arrays using array voltage and string currents. *Energy Convers. Manag.* **2018**, *178*, 250–264. [CrossRef]
88. Madeti, S.R.; Singh, S. Modeling of PV system based on experimental data for fault detection using kNN method. *Sol. Energy* **2018**, *173*, 139–151. [CrossRef]
89. Zhao, Q.; Shao, S.; Lu, L.; Liu, X.; Zhu, H. A new PV array fault diagnosis method using fuzzy C-mean clustering and fuzzy membership algorithm. *Energies* **2018**, *11*, 238. [CrossRef]
90. Lu, X.; Lin, P.; Cheng, S.; Lin, Y.; Chen, Z.; Wu, L.; Zheng, Q. Fault diagnosis for photovoltaic array based on convolutional neural network and electrical time series graph. *Energy Convers. Manag.* **2019**, *196*, 950–965. [CrossRef]
91. Appiah, A.Y.; Zhang, X.; Ayawli, B.B.K.; Kyeremeh, F. Long short-term memory networks based automatic feature extraction for photovoltaic array fault diagnosis. *IEEE Access* **2019**, *7*, 30089–30101. [CrossRef]
92. Chen, Z.; Chen, Y.; Wu, L.; Cheng, S.; Lin, P. Deep residual network based fault detection and diagnosis of photovoltaic arrays using current-voltage curves and ambient conditions. *Energy Convers. Manag.* **2019**, *198*, 111793. [CrossRef]
93. Cheng, Z.; Zhong, D.; Li, B.; Liu, Y. Research on fault detection of PV array based on data fusion and fuzzy mathematics. In Proceedings of the 2011 Asia-Pacific Power and Energy Engineering Conference, Wuhan, China, 25–28 March 2011; IEEE: Piscataway, NJ, USA, 2011; pp. 1–4.

94. Bonsignore, L.; Davarifar, M.; Rabhi, A.; Tina, G.M.; Elhajjaji, A. Neuro-fuzzy fault detection method for photovoltaic systems. *Energy Procedia* **2014**, *62*, 431–441. [CrossRef]
95. Hempelmann, S.; Feng, L.; Basoglu, C.; Behrens, G.; Diehl, M.; Friedrich, W.; Brandt, S.; Pfeil, T. Evaluation of unsupervised anomaly detection approaches on photovoltaic monitoring data. In Proceedings of the 2020 47th IEEE Photovoltaic Specialists Conference (PVSC), Calgary, AB, Canada, 15 June–21 August 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 2671–2674.
96. Kou, L.; Liu, C.; Cai, G.w.; Zhang, Z.; Li, X.j.; Yuan, Q.d. Fault diagnosis for power converters based on random forests and feature transformation. In Proceedings of the 2020 IEEE 9th International Power Electronics and Motion Control Conference (IPEMC2020-ECCE Asia), Nanjing, China, 29 November–2 December 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1821–1826.
97. Veerasamy, V.; Wahab, N.I.A.; Othman, M.L.; Padmanaban, S.; Sekar, K.; Ramachandran, R.; Hizam, H.; Vinayagam, A.; Islam, M.Z. LSTM recurrent neural network classifier for high impedance fault detection in solar PV integrated power system. *IEEE Access* **2021**, *9*, 32672–32687. [CrossRef]
98. Li, Z.; Gao, Y.; Zhang, X.; Wang, B.; Ma, H. A model-data-hybrid-driven diagnosis method for open-switch faults in power converters. *IEEE Trans. Power Electron.* **2020**, *36*, 4965–4970. [CrossRef]
99. Riley, D.; Johnson, J. Photovoltaic prognostics and heath management using learning algorithms. In Proceedings of the 2012 38th IEEE Photovoltaic Specialists Conference, Austin, TX, USA, 3–8 June 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 1535–1539.
100. De Benedetti, M.; Leonardi, F.; Messina, F.; Santoro, C.; Vasilakos, A. Anomaly detection and predictive maintenance for photovoltaic systems. *Neurocomputing* **2018**, *310*, 59–68. [CrossRef]
101. Samara, S.; Natsheh, E. Intelligent real-time photovoltaic panel monitoring system using artificial neural networks. *IEEE Access* **2019**, *7*, 50287–50299. [CrossRef]
102. Huuhtanen, T.; Jung, A. Predictive maintenance of photovoltaic panels via deep learning. In Proceedings of the 2018 IEEE Data Science Workshop (DSW), Lausanne, Switzerland, 4–6 June 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 66–70.
103. Betti, A.; Trovato, M.L.L.; Leonardi, F.S.; Leotta, G.; Ruffini, F.; Lanzetta, C. Predictive maintenance in photovoltaic plants with a big data approach. *arXiv* **2019**, arXiv:1901.10855.
104. Zulfauzi, I.A.; Dahlan, N.Y.; Sintuya, H.; Setthapun, W. Anomaly detection using K-Means and long-short term memory for predictive maintenance of large-scale solar (LSS) photovoltaic plant. *Energy Rep.* **2023**, *9*, 154–158. [CrossRef]
105. Marangis, D.; Livera, A.; Tziolis, G.; Makrides, G.; Kyprianou, A.; Georghiou, G.E. Trend-Based Predictive Maintenance and Fault Detection Analytics for Photovoltaic Power Plants. *Sol. RRL* **2024**, *8*, 2400473. [CrossRef]
106. Huang, Y.; Lu, J.; Liu, C.; Xu, X.; Wang, W.; Zhou, X. Comparative study of power forecasting methods for PV stations. In Proceedings of the 2010 International Conference on Power System Technology, Hangzhou, China, 24–28 October 2010; IEEE: Piscataway, NJ, USA, 2010; pp. 1–6.
107. Paoli, C.; Voyant, C.; Muselli, M.; Nivet, M.L. Forecasting of preprocessed daily solar radiation time series using neural networks. *Sol. Energy* **2010**, *84*, 2146–2160. [CrossRef]
108. Dahmani, K.; Dizene, R.; Notton, G.; Paoli, C.; Voyant, C.; Nivet, M.L. Estimation of 5-min time-step data of tilted solar global irradiation using ANN (Artificial Neural Network) model. *Energy* **2014**, *70*, 374–381. [CrossRef]
109. Brofferio, S.C.; Antonini, A.; Galimberti, G.; Galeri, D. A method for estimating and monitoring the power generated by a photovoltaic module based on supervised adaptive neural networks. In Proceedings of the 2011 IEEE International Conference on Smart Measurements of Future Grids (SMFG) Proceedings, Bologna, Italy, 14–16 November 2011; IEEE: Piscataway, NJ, USA, 2011; pp. 148–153.
110. Saberian, A.; Hizam, H.; Radzi, M.A.M.; Ab Kadir, M.; Mirzaei, M. Modelling and prediction of photovoltaic power output using artificial neural networks. *Int. J. Photoenergy* **2014**, *2014*, 469701. [CrossRef]
111. Pedro, H.T.; Coimbra, C.F. Short-term irradiance forecastability for various solar micro-climates. *Sol. Energy* **2015**, *122*, 587–602. [CrossRef]
112. Ramsami, P.; Oree, V. A hybrid method for forecasting the energy output of photovoltaic systems. *Energy Convers. Manag.* **2015**, *95*, 406–413. [CrossRef]
113. Bouquet, P.; Jackson, I.; Nick, M.; Kaboli, A. AI-based forecasting for optimised solar energy management and smart grid efficiency. *Int. J. Prod. Res.* **2024**, *62*, 4623–4644. [CrossRef]
114. Sivaneasan, B.; Yu, C.; Goh, K. Solar forecasting using ANN with fuzzy logic pre-processing. *Energy Procedia* **2017**, *143*, 727–732. [CrossRef]
115. Wang, F.; Zhang, Z.; Liu, C.; Yu, Y.; Pang, S.; Duić, N.; Shafie-Khah, M.; Catalao, J.P. Generative adversarial networks and convolutional neural networks based weather classification model for day ahead short-term photovoltaic power forecasting. *Energy Convers. Manag.* **2019**, *181*, 443–462. [CrossRef]
116. Lu, H.; Chang, G. A hybrid approach for day-ahead forecast of PV power generation. *IFAC-PapersOnLine* **2018**, *51*, 634–638. [CrossRef]
117. Ling, L.T.W.; Hwee, J.O. Intelligent Solar Energy Management through Human-Computer Interaction and Generative Adversarial Networks. *J. Sustain. Renew. Energy Innov. Pract.* **2025**, *1*, 16–29.

118. Wen, L.; Zhou, K.; Yang, S.; Lu, X. Optimal load dispatch of community microgrid with deep learning based solar power and load forecasting. *Energy* **2019**, *171*, 1053–1065. [CrossRef]
119. VanDeventer, W.; Jamei, E.; Thirunavukkarasu, G.S.; Seyedmahmoudian, M.; Soon, T.K.; Horan, B.; Mekhilef, S.; Stojcevski, A. Short-term PV power forecasting using hybrid GASVM technique. *Renew. Energy* **2019**, *140*, 367–379. [CrossRef]
120. Shirbhate, I.M.; Barve, S.S. Solar panel monitoring and energy prediction for smart solar system. *Int. J. Adv. Appl. Sci. ISSN* **2019**, *2252*, 8814. [CrossRef]
121. Sujatha, K.; Ponmagal, R.; Godhavari, T.; Kumar, K.R. Automation of solar system for maximum power point tracking using artificial neural networks and IoT. In Proceedings of the 2016 IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics Engineering (UPCON), Varanasi, India, 9–11 December 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 61–66.
122. Tharakan, R.A.; Joshi, R.; Ravindran, G.; Jayapandian, N. Machine learning approach for automatic solar panel direction by using naïve bayes algorithm. In Proceedings of the 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 6–8 May 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 1317–1322.
123. Sharifzadeh, M.; Sikinioti-Lock, A.; Shah, N. Machine-learning methods for integrated renewable power generation: A comparative study of artificial neural networks, support vector regression, and Gaussian Process Regression. *Renew. Sustain. Energy Rev.* **2019**, *108*, 513–538. [CrossRef]
124. Galván, I.M.; Valls, J.M.; Cervantes, A.; Aler, R. Multi-objective evolutionary optimization of prediction intervals for solar energy forecasting with neural networks. *Inf. Sci.* **2017**, *418*, 363–382. [CrossRef]
125. Al-Omary, M.; Aljarrah, R.; Albatayneh, A.; Alzaareer, K.; Malkawi, A.; Jaradat, H. Optimal neural network for predicting solar energy in sensor units based on a cascaded input/structure direct optimization. *J. Sensors* **2022**, *2022*, 7273469. [CrossRef]
126. Kaur, D.; Islam, S.N.; Mahmud, M.A.; Haque, M.E.; Anwar, A. A VAE-Bayesian deep learning scheme for solar power generation forecasting based on dimensionality reduction. *Energy AI* **2023**, *14*, 100279. [CrossRef]
127. Ali, M.; Paracha, M.K. An IoT based approach for monitoring solar power consumption with Adafruit Cloud. *Int. J. Eng. Appl. Sci. Technol.* **2020**, *4*, 335–341. [CrossRef]
128. Aghenta, L.O.; Iqbal, M.T. Development of an IoT based open source SCADA system for PV system monitoring. In Proceedings of the 2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE), Edmonton, AB, Canada, 5–8 May 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1–4.
129. Gupta, A.; Jain, R.; Joshi, R.; Saxena, R. Real time remote solar monitoring system. In Proceedings of the 2017 3rd International Conference on Advances in Computing, Communication & Automation (ICACCA) (Fall), Dehradun, India, 15–16 September 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–5.
130. Gupta, V.; Sharma, M.; Pachauri, R.K.; Babu, K.D. A low-cost real-time IOT enabled data acquisition system for monitoring of PV system. *Energy Sour. Part A Recover. Util. Environ. Eff.* **2021**, *43*, 2529–2543. [CrossRef]
131. Pereira, R.I.; Dupont, I.M.; Carvalho, P.C.; Juca, S.C. IoT embedded linux system based on Raspberry Pi applied to real-time cloud monitoring of a decentralized photovoltaic plant. *Measurement* **2018**, *114*, 286–297. [CrossRef]
132. Shapsough, S.; Takrouri, M.; Dhaouadi, R.; Zualkernan, I.A. Using IoT and smart monitoring devices to optimize the efficiency of large-scale distributed solar farms. *Wirel. Netw.* **2021**, *27*, 4313–4329. [CrossRef]
133. Lakshmi, K.; Latha, H. Design and Development of Remote Monitoring Solar Powered Agricultural Motor Pump Using Modbus and MQTT IOT. In Proceedings of the 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE), Ballari, India, 2–3 November 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–5.
134. Deenadayalan, K.D.; Arunraja, A.; Jayanthy, S.; Selvaraj, S. IoT based remote monitoring of mass solar panels. In Proceedings of the 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2–4 July 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1009–1014.
135. Gimeno-Sales, F.J.; Orts-Grau, S.; Escribá-Aparisi, A.; González-Altozano, P.; Balbastre-Peralta, I.; Martínez-Márquez, C.I.; Gasque, M.; Seguí-Chilet, S. PV monitoring system for a water pumping scheme with a lithium-ion battery using free open-source software and IoT technologies. *Sustainability* **2020**, *12*, 10651. [CrossRef]
136. Mohammed, M.I.; Al-Naib, A.M.I. Web Server Based Data Monitoring System of PV Panels Using S7-1200 PLC. *NTU J. Renew. Energy* **2023**, *5*, 103–111. [CrossRef]
137. Karthick, A.; Abarna, C.; Robin, R.D.; Khan, N.H.; Janani, J. Low-Cost Energy Monitoring of gird Connected Solar Photovoltaic Systems. In Proceedings of the 2024 IEEE Third International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, India, 26–28 April 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 891–894.
138. Calderón, D.; Folgado, F.J.; González, I.; Calderón, A.J. Implementation and Experimental Application of Industrial IoT Architecture Using Automation and IoT Hardware/Software. *Sensors* **2024**, *24*, 8074. [CrossRef]
139. Kodali, R.K.; John, J. Smart Monitoring of Solar Panels Using AWS. In Proceedings of the 2020 International Conference on Power Electronics & IoT Applications in Renewable Energy and Its Control (PARC 2020), Mathura, India, 28–29 February 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 422–427.

140. Paredes-Parra, J.M.; García-Sánchez, A.J.; Mateo-Aroca, A.; Molina-García, Á. An alternative internet-of-things solution based on LOra for PV power plants: Data monitoring and management. *Energies* **2019**, *12*, 881. [CrossRef]
141. Al-Naib, A.M.I.; Mohammed, M.I. IoT-Based Real Time Data Acquisition of PV Panel. In Proceedings of the 2023 International Conference on Engineering, Science and Advanced Technology (ICESAT 2023), Mosul, Iraq, 21–22 June 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 169–173.
142. Spanias, A.S. Solar Energy Management as an Internet of Things (IoT) Application. In Proceedings of the 2017 8th International Conference on Information, Intelligence, Systems & Applications (IISA 2017), Larnaca, Cyprus, 27–30 August 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–4.
143. Shweta, R.; Sivagnanam, S.; Kumar, K.A. Fault detection and monitoring of solar photovoltaic panels using internet of things technology with fuzzy logic controller. *Electr. Eng. Electromech.* **2022**, *6*, 67–74. [CrossRef]
144. Kekre, A.; Gawre, S.K. Solar Photovoltaic Remote Monitoring System Using IoT. In Proceedings of the 2017 International Conference on Recent Innovations in Signal Processing and Embedded Systems (RISE 2017), Bhopal, India, 27–29 October 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 619–623.
145. Adhya, S.; Saha, D.; Das, A.; Jana, J.; Saha, H. An IoT based smart solar photovoltaic remote monitoring and control unit. In Proceedings of the 2016 2nd International Conference on Control, Instrumentation, Energy & Communication (CIEC), Kolkata, India, 28–30 January 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 432–436.
146. Emamian, M.; Eskandari, A.; Aghaei, M.; Nedaei, A.; Sizkouhi, A.M.; Milimonfared, J. Cloud computing and IoT based intelligent monitoring system for photovoltaic plants using machine learning techniques. *Energies* **2022**, *15*, 3014. [CrossRef]
147. Shakya, S. A self monitoring and analyzing system for solar power station using IoT and data mining algorithms. *J. Soft Comput. Paradig.* **2021**, *3*, 96–109. [CrossRef]
148. Suresh, M.; Meenakumari, R.; Kumar, R.A.; Raja, T.A.S.; Mahendran, K.; Pradeep, A. Fault detection and monitoring of solar pv panels using internet of things. *Int. J. Ind. Eng.* **2018**, *2*, 146–149.
149. Del Río, A.M.; Ramírez, I.S.; Márquez, F.P.G. Photovoltaic Solar Power Plant Maintenance Management Based on IoT and Machine Learning. In Proceedings of the 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT 2021), Zallaq, Bahrain, 29–30 September 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 423–428.
150. Kingsley-Amaehule, M.; Uhunmwangho, R.; Nwazor, N.; Okedu, K.E. Smart Intelligent Monitoring and Maintenance Management of Photo-voltaic Systems. *Int. J. Smart Grid* **2022**, *6*, 110–122.
151. Mellit, A.; Hamied, A.; Lughi, V.; Pavan, A.M. A Low-Cost Monitoring and Fault Detection System for Stand-Alone Photovoltaic Systems Using IoT Technique. In Proceedings of the 13th International Conference of the IMACS TC1 Committee (ELECTRIMACS 2019), Salerno, Italy, 21–23 May 2019; Springer: Cham, Switzerland, 2020; pp. 349–358.
152. Li, Y.; Lin, P.; Zhou, H.; Chen, Z.; Wu, L.; Cheng, S.; Su, F. On-line monitoring system of PV array based on internet of things technology. *IOP Conf. Ser. Earth Environ. Sci.* **2017**, *93*, 012078. [CrossRef]
153. Xia, K.; Ni, J.; Ye, Y.; Xu, P.; Wang, Y. A real-time monitoring system based on ZigBee and 4G communications for photovoltaic generation. *CSEE J. Power Energy Syst.* **2020**, *6*, 52–63.
154. Nalamwar, H.; Ivanov, M.A.; Baidali, S. Automated intelligent monitoring and the controlling software system for solar panels. *IOP Conf. Ser. Earth Environ. Sci.* **2017**, *803*, 012107. [CrossRef]
155. Hamied, A.; Boubidi, A.; Rouibah, N.; Chine, W.; Mellit, A. IoT-Based Smart Photovoltaic Arrays for Remote Sensing and Fault Identification. In Proceedings of the International Conference on Artificial Intelligence in Renewable Energetic Systems (IC-AIRES 2019), Taghit-Bechar, Algeria, 26–28 November 2019; Springer: Cham, Switzerland, 2020; pp. 478–486.
156. Priharti, W.; Rosmawati, A.; Wibawa, I. IoT based photovoltaic monitoring system application. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *1367*, 012069. [CrossRef]
157. Cheddadi, Y.; Cheddadi, H.; Cheddadi, F.; Errahimi, F.; Es-sbai, N. Design and implementation of an intelligent low-cost IoT solution for energy monitoring of photovoltaic stations. *SN Appl. Sci.* **2020**, *2*, 1165. [CrossRef]
158. Malik, H.; Alsabban, M.; Qaisar, S.M. Arduino based automatic solar panel dust disposition estimation and cloud based reporting. *Procedia Comput. Sci.* **2021**, *194*, 102–113. [CrossRef]
159. Narvios, W.M.O.; Nguyen, Y. IoT based detection, monitoring and automatic cleaning system for soiling of PV solar panel. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *2406*, 060005.
160. Ul Mehmood, M.; Ulasyar, A.; Ali, W.; Zeb, K.; Zad, H.S.; Uddin, W.; Kim, H.J. A new cloud-based IoT solution for soiling ratio measurement of PV systems using artificial neural network. *Energies* **2023**, *16*, 996. [CrossRef]
161. Adila, A.S.; Husam, A.; Husi, G. Towards the Self-Powered Internet of Things (IoT) by Energy Harvesting: Trends and Technologies for Green IoT. In Proceedings of the 2018 2nd International Symposium on Small-Scale Intelligent Manufacturing Systems (SIMS), Cavan, Ireland, 16–18 April 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–5.
162. Podder, A.K.; Roy, N.K.; Pota, H.R. MPPT methods for solar PV systems: A critical review based on tracking nature. *IET Renew. Power Gener.* **2019**, *13*, 1615–1632. [CrossRef]

163. Rokonuzzaman, M.; Shakeri, M.; Hamid, F.A.; Mishu, M.K.; Pasupuleti, J.; Rahman, K.S.; Tiong, S.K.; Amin, N. Iot-enabled high efficiency smart solar charge controller with maximum power point tracking—Design, hardware implementation and performance testing. *Electronics* **2020**, *9*, 1267. [CrossRef]
164. Williams, K.; Qouneh, A. Internet of Things: Solar Array Tracker. In Proceedings of the 2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS), Boston, MA, USA, 6–9 August 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1057–1060.
165. Parveen, R.; Mohammed, A.M.; Ravinder, K. IoT based solar tracking system for efficient power generation. *Int. J. Res. Anal. Rev.* **2018**, *5*, 481–485.
166. Shah, M.M.A.; Parvez, M.S.; Ahmed, A.; Hazari, M.R. IoT Based Power Monitoring of Solar Panel Incorporating Tracking System. In Proceedings of the 2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI), Rajshahi, Bangladesh, 8–9 July 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 1–4.
167. Dandu, R.; Thangam, S. IoT Based Single Axis Solar Tracker. In Proceedings of the 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), New Delhi, India, 6–8 July 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–5.
168. Singh, A.; Kundu, S.; Shukla, N.; Gupta, S. IoT based weather monitoring system using sun tracking solar panel. *Int. J. VLSI Des. Technol.* **2019**, *5*, 12–17.
169. Divakaran, R.; Nandini, G.; Pavithra, N.; Priya, D.; Dharshini, B. IoT based automatic control of sun tracking solar panel for high power generation. In Proceedings of the First International Conference on Advanced Scientific Innovation in Science, Engineering and Technology, ICASISET 2020, Chennai, India, 16–17 May 2020.
170. Yakut, M.; Erturk, N.B. An IoT-based approach for optimal relative positioning of solar panel arrays during backtracking. *Comput. Stand. Interfaces* **2022**, *80*, 103568. [CrossRef]
171. Kumar, K.; Varshney, L.; Ambikapathy, A.; Mittal, V.; Prakash, S.; Chandra, P.; Khan, N. Soft computing and IoT based solar tracker. *Int. J. Power Electron. Drive Syst.* **2021**, *12*, 1880. [CrossRef]
172. Gbadamosi, S.L. Design and implementation of IoT-based dual-axis solar PV tracking system. *Electrotech. Rev.* **2021**, *97*, 57–62. [CrossRef]
173. Said, M.; Jumaat, S.A.; Jawa, C.R.A. Dual axis solar tracker with IoT monitoring system using arduino. *Int. J. Power Electron. Drive Syst* **2020**, *11*, 451–458.
174. Hammas, M.; Fituri, H.; Shour, A.; Khan, A.A.; Khan, U.A.; Ahmed, S. A Hybrid Dual-Axis Solar Tracking System: Combining Light-Sensing and Time-Based GPS for Optimal Energy Efficiency. *Energies* **2025**, *18*, 217. [CrossRef]
175. Hachicha, A.A.; Al-Sawafta, I.; Said, Z. Impact of dust on the performance of solar photovoltaic (PV) systems under United Arab Emirates weather conditions. *Renew. Energy* **2019**, *141*, 287–297. [CrossRef]
176. Sulaiman, S.A.; Hussain, H.H.; Leh, N.; Razali, M.S. Effects of dust on the performance of PV panels. *World Acad. Sci. Eng. Technol.* **2011**, *58*, 588–593.
177. Rao, A.; Pillai, R.; Mani, M.; Ramamurthy, P. Influence of dust deposition on photovoltaic panel performance. *Energy Procedia* **2014**, *54*, 690–700. [CrossRef]
178. Rajput, D.S.; Sudhakar, K. Effect of dust on the performance of solar PV panel. *Int. J. ChemTech Res.* **2013**, *5*, 1083–1086.
179. Kadir, J.; Ismarrubie, Z.; Yussof, H.; Hasan, W.Z.W. Development of IoT Based Dust Density and Solar Panel Efficiency Monitoring System. In Proceedings of the 2021 International Conference on Electrical, Computer and Energy Technologies (ICECET), Cape Town, South Africa, 9–10 December 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 1–6.
180. Suhaimi, S.N.A.M.; Jasmie, M.N.; Zambri, N.A.; Hassan, O.A.; Mustafa, F.; Yi, S.S.; Salim, N. Smart Solar Photovoltaic Panel Dust Monitoring System Using Internet of Thing (IoT). *J. Adv. Res. Appl. Mech.* **2024**, *123*, 15–30. [CrossRef]
181. Abdolzadeh, M.; Ameri, M. Improving the effectiveness of a photovoltaic water pumping system by spraying water over the front of photovoltaic cells. *Renew. Energy* **2009**, *34*, 91–96. [CrossRef]
182. Majeed, R.; Waqas, A.; Sami, H.; Ali, M.; Shahzad, N. Experimental investigation of soiling losses and a novel cost-effective cleaning system for PV modules. *Sol. Energy* **2020**, *201*, 298–306. [CrossRef]
183. Jawale, J.; Karra, V.; Patil, B.; Singh, P.; Singh, S.; Atre, S. Solar Panel Cleaning Bot for Enhancement of Efficiency—An Innovative Approach. In Proceedings of the 2016 3rd International Conference on Devices, Circuits and Systems (ICDCS), Coimbatore, India, 3–5 March 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 103–108.
184. Parrott, B.; Zanini, P.C.; Shehri, A.; Kotsovos, K.; Gereige, I. Automated, robotic dry-cleaning of solar panels in Thuwal, Saudi Arabia using a silicone rubber brush. *Sol. Energy* **2018**, *171*, 526–533. [CrossRef]
185. Alagoz, S.; Apak, Y. Removal of spoiling materials from solar panel surfaces by applying surface acoustic waves. *J. Clean. Prod.* **2020**, *253*, 119992. [CrossRef]
186. Aly, S.P.; Gandhidasan, P.; Barth, N.; Ahzi, S. Novel Dry Cleaning Machine for Photovoltaic and Solar Panels. In Proceedings of the 2015 3rd International Renewable and Sustainable Energy Conference (IRSEC), Marrakech, Morocco, 10–13 December 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 1–6.

187. Mobin, S.T. Design and Development of Solar Panel Cleaning System. Ph.D. Thesis, National Institute of Technology Rourkela, Rourkela, Odisha, India, 2015.
188. Memon, N.K. Autonomous Vehicles for Cleaning Solar Panels. In Proceedings of the 2016 International Renewable and Sustainable Energy Conference (IRSEC), Marrakech, Morocco, 14–17 November 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 633–637.
189. Raju, L.; Gokulakrishnan, S.; Muthukumar, P.R.; Jagannathan, S.; Morais, A.A. IoT Based Autonomous Demand Side Management of a Micro-Grid Using Arduino and Multi Agent System. In Proceedings of the 2017 International Conference on Power and Embedded Drive Control (ICPEDC), Chennai, India, 16–18 March 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 44–49.
190. Pradeep, S.; Krishna, S.; Reddy, M.S.; Sri, D.D.; Sri, M.S. Analysis and Functioning of Smart Grid for Enhancing Energy Efficiency Using Optimization Techniques with IoT. In Proceedings of the 2023 IEEE 5th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA), Hamburg, Germany, 7–8 October 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 316–321.
191. Joshua, S.R.; Junghyun, Y.; Park, S.; Kwon, K. Integrating Deep Learning and Energy Management Standards for Enhanced Solar–Hydrogen Systems: A Study Using MobileNetV2, InceptionV3, and ISO 50001: 2018. *Hydrogen* **2024**, *5*, 819–850. [CrossRef]
192. International Organization for Standardization. *ISO 50001:2018—Energy Management Systems—Requirements with Guidance for Use*; ISO: Geneva, Switzerland, 2018. Available online: https://www.iso.org/standard/69426.html (accessed on 10 April 2025).
193. Rojek, I.; Mikołajewski, D.; Mroziński, A.; Macko, M.; Bednarek, T.; Tyburek, K. Internet of Things Applications for Energy Management in Buildings Using Artificial Intelligence—A Case Study. *Energies* **2025**, *18*, 1706. [CrossRef]
194. Ramli, R.M.; Jabbar, W.A. Design and implementation of solar-powered with IoT-Enabled portable irrigation system. *Internet Things Cyber-Phys. Syst.* **2022**, *2*, 212–225. [CrossRef]
195. Rochd, A.; Benazzouz, A.; Ait Abdelmoula, I.; Raihani, A.; Ghennioui, A.; Naimi, Z.; Ikken, B. Design and implementation of an AI-based & IoT-enabled Home Energy Management System: A case study in Benguerir—Morocco. *Energy Rep.* **2021**, *7*, 699–719.
196. Cardinale-Villalobos, L.; Jimenez-Delgado, E.; García-Ramírez, Y.; Araya-Solano, L.; Solís-García, L.A.; Méndez-Porras, A.; Alfaro-Velasco, J. IoT system based on artificial intelligence for hot spot detection in photovoltaic modules for a wide range of irradiances. *Sensors* **2023**, *23*, 6749. [CrossRef]
197. Menaka, C.; Awasthi, A.; Yadav, D.C.; Jain, S.K. Designing a Renewable Energy System for Industrial IoT with Artificial Intelligence. In Proceedings of the E3S Web of Conferences, 1st International Conference on Power and Energy Systems (ICPES 2023), Madurai, India, 23 November 2023; EDP Sciences: Les Ulis, France, 2024; Volume 540, p. 13008.
198. Mostakim, M.A.; Baki, A.A.; Hossen, M.S.; Imran, M.A.; Fathah, A.A.; Alam, K.; Mahmud, U. Optimization of Solar PV Efficiency & Cleaning Schedule Using AI and IoT Sensors. *SSRN* **2024**. [CrossRef]
199. Raza, A.; Baloch, M.H.; Ali, I.; Ali, W.; Hassan, M.; Karim, A. Artificial Intelligence and IoT-Based Autonomous Hybrid Electric Vehicle with Self-Charging Infrastructure. In Proceedings of the 2022 International Conference on Emerging Technologies in Electronics, Computing and Communication (ICETECC), Jamshoro, Sindh, Pakistan, 7–9 December 2022; IEEE: Piscataway, NJ, USA, 2022; pp. 1–6.

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