

Article

Anomaly Prediction in Solar Photovoltaic (PV) Systems via Rayleigh Distribution with Integrated Internet of Sensing Things (IoST) Monitoring and Dynamic Sun-Tracking

Tajim Md. Niamat Ullah Akhund ^{1,2,*} , Nafisha Tamanna Nice ¹, Muftain Ahmed Joy ¹, Tanvir Ahmed ¹ and Md Whaiduzzaman ^{3,4,*} 

- ¹ Department of CSE, Daffodil International University, Dhaka 1216, Bangladesh; nafisha15-1837@diu.edu.bd (N.T.N.); muftain15-1849@diu.edu.bd (M.A.J.); tanvir15-1939@diu.edu.bd (T.A.)
² Graduate School of Science and Engineering, Saga University, Saga 8408502, Japan
³ School of Information Systems, Queensland University of Technology, Brisbane 4000, Australia
⁴ Design and Creative Technology, Torrens University, Brisbane 4006, Australia
* Correspondence: tajim.cse@diu.edu.bd (T.M.N.U.A.); md.whaiduzzaman@torrens.edu.au (M.W.)

Abstract: The proliferation of solar panel installations presents significant societal and environmental advantages. However, many panels are situated in remote or inaccessible locations, like rooftops or vast desert expanses. Moreover, monitoring individual panel performance in large-scale systems poses a logistical challenge. Addressing this issue necessitates an efficient surveillance system leveraging wide area networks. This paper introduces an Internet of Sensing Things (IoST)-based monitoring system integrated with sun-tracking capabilities for solar panels. Cutting-edge sensors and microcontrollers collect real-time data and securely store it in a cloud-based server infrastructure, enabling global accessibility and comprehensive analysis for future optimization. Innovative techniques are proposed to maximize power generation from sunlight radiation, achieved through continuous panel alignment with the sun's position throughout the day. A solar tracking mechanism, utilizing light-dependent sensors and servo motors, dynamically adjusts panel orientation based on the sun's angle of elevation and direction. This research contributes to the advancement of efficient and sustainable solar energy systems. Integrating state-of-the-art technologies ensures reliability and effectiveness, paving the way for enhanced performance and the widespread adoption of solar energy. Additionally, the paper explores anomaly prediction using Rayleigh distribution, offering insights into potential irregularities in solar panel performance.

Keywords: Internet of Sensing Things (IoST); Internet of Things (IoT); solar panel monitoring; sensors network; anomaly prediction; Rayleigh distribution



Citation: Akhund, T.M.N.U.; Nice, N.T.; Joy, M.A.; Ahmed, T.; Whaiduzzaman, M. Anomaly Prediction in Solar Photovoltaic (PV) Systems via Rayleigh Distribution with Integrated Internet of Sensing Things (IoST) Monitoring and Dynamic Sun-Tracking. *Information* **2024**, *15*, 451. <https://doi.org/10.3390/info15080451>

Academic Editor: Zahir M. Hussain

Received: 23 June 2024

Revised: 28 July 2024

Accepted: 29 July 2024

Published: 1 August 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The growing global emphasis on sustainable energy sources has led to a substantial increase in the adoption of solar energy systems. As a pivotal technology in harnessing solar energy, solar panels have gained widespread utilization across various applications. However, to maximize the efficiency and effectiveness of solar energy systems, it is crucial to optimize the performance of solar panels. One significant challenge in this domain is ensuring that solar panels consistently receive maximum sunlight exposure throughout the day. Traditional fixed solar panels often fail to capture optimal sunlight, producing suboptimal amounts of energy. This challenge underscores the importance of solar tracking systems, which adjust the orientation of solar panels to follow the sun's path, thereby maximizing energy capture.

The motivation behind this study stems from the need to enhance the efficiency of solar energy systems through innovative technological solutions. With the advent of the Internet of Things (IoT) and smart technologies, there is a significant opportunity to

develop advanced monitoring and control systems for solar panels. Such systems can provide real-time data on various parameters affecting solar panel performance, enabling timely adjustments and predictive maintenance. This study aims to leverage IoT technology to design and implement an intelligent solar panel tracking and monitoring system, thereby addressing the inefficiencies of traditional fixed solar panels.

The Internet of Sensing Things (IoST) refers to a network of interconnected sensing devices that collect and exchange data through the Internet. These devices, often equipped with sensors, can monitor various physical or environmental conditions, such as temperature, humidity, light intensity, and motion. IoST extends the concept of the Internet of Things (IoT) by emphasizing the sensing aspect, enabling real-time data collection, analysis, and response. This technology facilitates smarter decision-making, automation, and improved efficiency in various applications, including environmental monitoring, healthcare, industrial processes, and smart cities. Dynamic sun-tracking refers to the use of automated systems to continuously adjust the orientation of solar panels or other solar energy collection devices to follow the movement of the sun across the sky throughout the day. Unlike static systems that remain fixed, dynamic sun-tracking systems utilize motors, sensors, and control algorithms to optimize the angle of the panels, ensuring they are always perpendicular to the sun's rays. This maximizes the amount of solar energy captured, increasing the efficiency and output of the solar power system. There are typically two types of dynamic sun-tracking systems: single-axis, which adjusts the panel's tilt in one direction, and dual-axis, which adjusts the tilt in two directions, providing even greater accuracy in tracking the sun's position. The primary objectives of this study are threefold and are as follows:

1. To develop an IoT-based solar panel tracking system that dynamically adjusts solar panels' orientation to maximize sunlight exposure.
2. To implement a comprehensive monitoring system that provides real-time data on key performance metrics, including temperature, humidity, voltage, current, and light intensity.
3. To evaluate the performance of the proposed system through experimental testing and comparative analysis with non-tracking solar panels, demonstrating the efficiency gains and potential for anomaly detection.

The contributions of this study are significant and multifaceted. Firstly, the development of an Arduino-based solar panel tracking system utilizing light-dependent resistors (LDRs) and servo motors offers a practical and cost-effective solution for maximizing solar energy capture. Secondly, the integration of NodeMCU (microcontroller unit) and the Thingspeak platform provides robust real-time monitoring capabilities, enabling users to access and analyze performance data remotely. This facilitates informed decision-making and proactive maintenance, enhancing the overall reliability of solar energy systems. Thirdly, the experimental results, obtained through rigorous testing in real-world conditions, provide empirical evidence of the efficiency gains achieved through solar tracking. The study demonstrates a substantial increase in power gain, validating the effectiveness of the proposed system.

In summary, this study addresses a critical need in the field of solar energy by developing and validating an innovative IoT-based solar panel tracking and monitoring system. By optimizing the orientation of solar panels and providing real-time performance data, the proposed system significantly enhances the efficiency and reliability of solar energy generation. This work contributes to the broader goal of advancing sustainable energy technologies and underscores the potential of IoT solutions in revolutionizing solar energy systems.

2. Literature Review

2.1. Previous Research

There exists a vast body of literature on solar panel monitoring and tracking systems. The total number of research works found on Google Scholar on related topics in the last two decades is illustrated in Figure 1. Figure 2 illustrates the word cloud among the related

research works found on Google Scholar in the last two decades. The size of each word corresponds to its frequency. Figure 3 illustrates the top keyword network among the related research works found on Google Scholar in the last two decades. To draw this network map, all the studied articles and their keywords were analyzed. Figures 1–3 are made with the collected data from the literature survey, using Python v3 programming data visualization, which shows the research trends and keyword importance among the related fields.

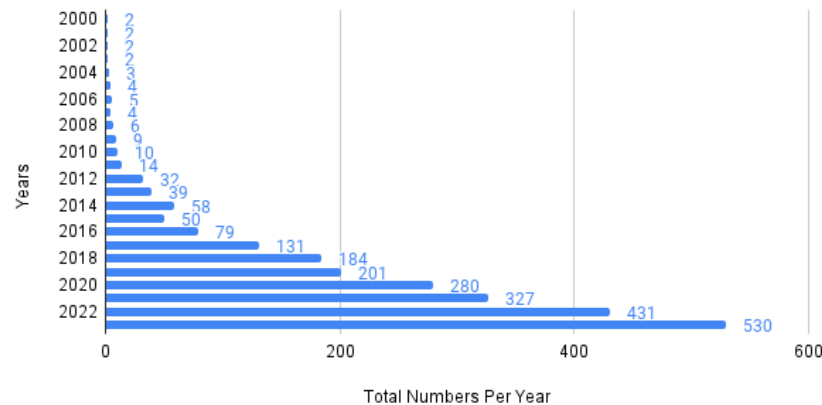


Figure 1. The total number of research works found on Google Scholar on related topics in the last two decades.

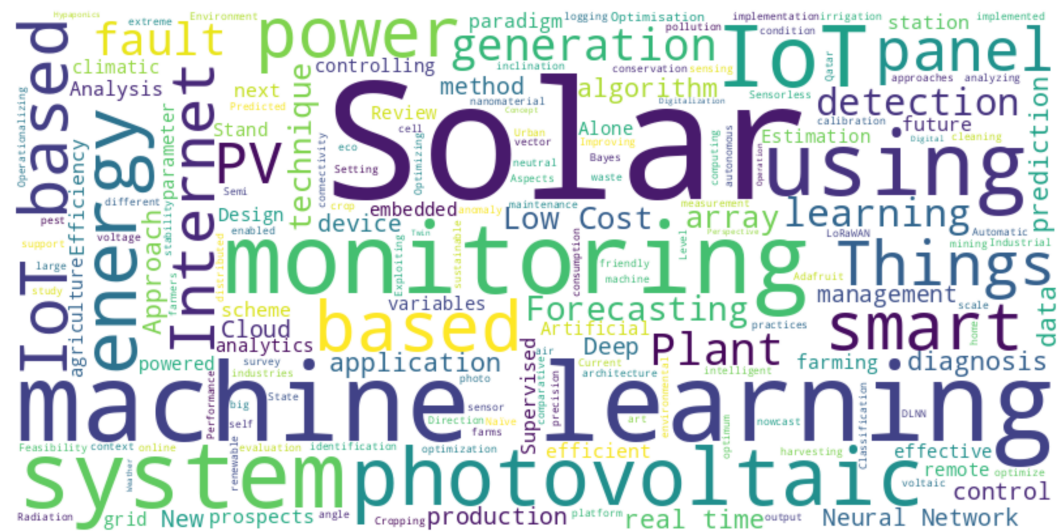


Figure 2. Word cloud of the related research works found on Google Scholar in the last two decades (the size of each word corresponds to its frequency).

Several studies have demonstrated the efficacy of IoT in solar panel monitoring. For instance, Guerrero et al. developed an IoT-based monitoring system that enables the remote tracking of solar panel performance, highlighting improvements in energy efficiency and maintenance response times [1]. Similarly, Suresh et al. proposed a cloud-based monitoring system that collects data from various sensors and uploads it to a cloud platform for real-time analysis and visualization, thereby enhancing decision-making processes for maintenance and optimization [2]. Wireless sensor networks (WSNs) play a crucial role in these monitoring systems. Chowdhury and Rahman designed a WSN-based solar panel monitoring system that ensures reliable data transmission and reduces the power consumption of the sensors, which is critical for remote and off-grid solar installations [3]. Moreover, the integration of machine learning algorithms into these systems has been explored by Ahmad et al., who utilized predictive analytics to forecast potential failures and optimize energy output, thus demonstrating significant advancements in predictive

maintenance capabilities [4]. Recent advancements also include the development of mobile applications that interface with monitoring systems, providing users with accessible and user-friendly platforms to monitor and control their solar installations. As highlighted by Kaur and Kaur, mobile applications can facilitate user engagement and improve the overall user experience by offering intuitive dashboards and real-time alerts [5]. The Internet of Things (IoT) has become a pervasive technology, with applications spanning various domains. Gawre and Kekre [6] showed connectivity among multiple devices and sensors within a unified network for solar monitoring. This architecture facilitates remote data access and device control from any location with internet connectivity. Data transmission over the Internet is facilitated through a GPRS-compatible modem. The authors of [7] introduced an innovative method for robotic arm control and anomaly prediction. Similarly, a proposed system [8] incorporates a multi-sensor network. Notably, voltage and current detection utilize a voltage divider, shunt, differential amplifier, potential transformer, and current transformer. Communication between the data logger and server is achieved via a GSM or GPRS “SIM900” module (made in China). The system aims to improve energy efficiency and enable the real-time monitoring of solar power consumption [9]. It leverages ADAFRUIT cloud services for data storage and communication, with sensor data analyzed by an Arduino (version R3) system. Connectivity is facilitated by a Wi-Fi Module, enabling data transmission to a cloud server for user access. The authors of [10] introduced an IoT-based system to help virus-affected people. This work emphasizes the role of IoT in enhancing accessibility and addressing societal challenges. The authors of [11] showed the evolution and emerging trends of IoT technologies and applications. The authors of [12] proposed a low-cost smartphone-controlled remote sensing IoT robot, showcasing the versatility and accessibility of IoT solutions for remote monitoring and automation tasks. Priharti et al. [13] demonstrated the real-time monitoring of a solar photovoltaic system, achieving high data accuracy. These efforts collectively underscore the potential of IoT-based solutions in revolutionizing solar energy monitoring and management. In [12,14], the authors presented a cost-effective health screening system, highlighting the versatility of IoT in healthcare applications. Phung et al. [15] implemented a reliable IoT-based system for managing solar energy in micro-grids, ensuring fault tolerance and self-recovery operations. Similarly, various studies have explored related topics, such as smart solar panel cleaning systems [16], remote monitoring of mass solar panels [17], efficiency improvements [18], monitoring with low power [19], smart monitoring schemes [20], and smart solar photovoltaic remote monitoring systems [21]. An LDR sensor was used by the authors of [22] for fault monitoring and control systems. A virtual approach has been developed, facilitating optimal performance and maintenance, by the authors of [23]. Moreover, weather monitoring systems [24] and SMS notification systems [25] have been proposed to enhance data collection and communication in IoT-based monitoring systems, demonstrating the versatility and potential impact of such technologies. The comparison of existing systems and the proposed IoST-based system highlights various novel features and enhancements. Mishra et al. (2020) [26] focused on IoT-based monitoring, while Haligaswatta et al. (2019) [27] explored solar tracking using fuzzy logic controllers. Chen et al. (2018) [28] emphasized predictive analytics for optimization, and Khalil et al. (2017) [29] utilized Arduino and GPS modules for solar tracking. Carrasco et al. (2016) [30] introduced dual-axis solar tracking for maximizing energy yield. Mellit and Kalogirou (2021) [31] combined artificial intelligence and IoT for the enhanced diagnosis and remote sensing of solar photovoltaic (PV) systems, and Badave et al. (2018) [32] developed an IoT-based health monitoring system for solar PV panels. Nath et al. (2023) [33] provided a comprehensive review on IoT integration with solar energy applications, and Mostofa and Islam (2023) [34] created an IoT system for live and remote monitoring of solar PV facilities. AlMallahi et al. (2023) [35] conducted a bibliometric analysis and highlighted global publication trends in IoT and solar energy.

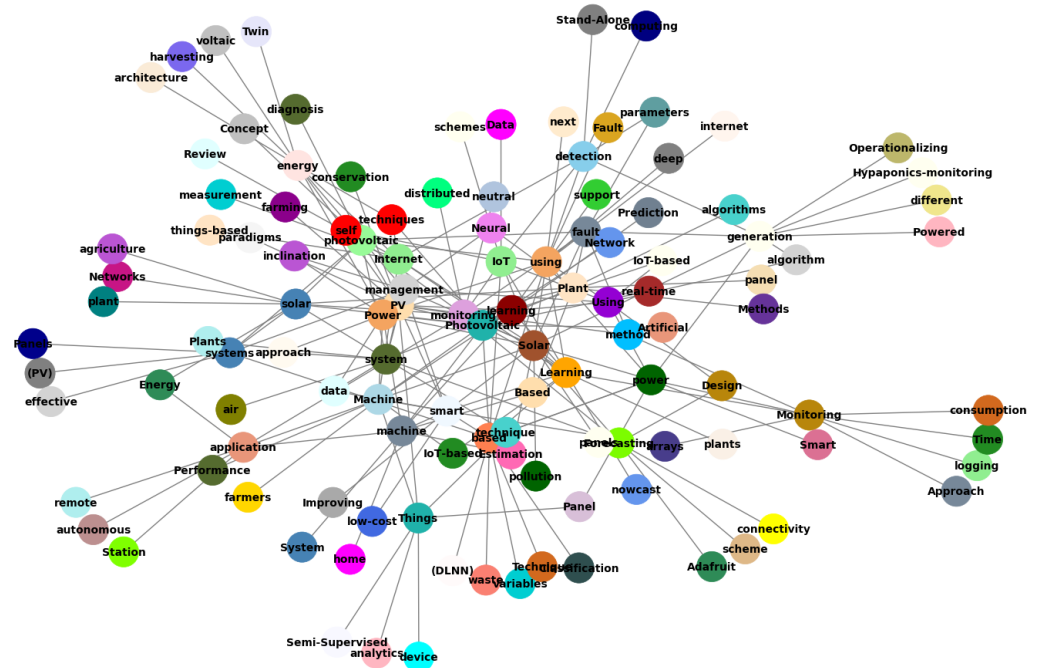


Figure 3. Top keywords network among the related research works found on Google Scholar in the last two decades.

The proposed IoST-based system extends functionality to include solar tracking capabilities by integrating light-dependent sensors and servo motors for precise panel orientation. It offers real-time monitoring and tracking, scalability, and remote accessibility through cloud integration within a scalable IoST framework. This system emphasizes ease of deployment and integration, making it suitable for widespread adoption in various settings. Additionally, it proposes a novel approach to predict abnormalities in solar panel output, which allows for the easy detection of defective solar panels within a large grid.

2.2. Comparison with Existing Systems and Novelty of the Proposed System

The proposed advancement in solar energy systems, driven by Internet of Sensing Things (IoST)-based technology, presents several innovative features and enhancements compared to existing systems; while previous works, such as Mishra et al. (2020) [26], focused primarily on IoT-based monitoring, our system extends functionality to include solar-tracking capabilities, thereby enhancing energy optimization beyond mere observation. Similarly, Haligaswatta et al. (2019) [27] explored solar tracking using fuzzy logic controllers, whereas our approach integrates light-dependent sensors and servo motors for precise panel orientation, providing a cost-effective yet efficient alternative. Additionally, Chen et al. (2018) [28] emphasized predictive analytics for optimization, while our system complements this by offering real-time monitoring and tracking, ensuring continuous performance enhancement. Furthermore, Khalil et al. (2017) [29] utilized Arduino and GPS modules for solar tracking. Still, our IoST-based solution offers scalability and remote accessibility through cloud integration, catering to diverse monitoring needs. Finally, Carasco et al. (2016) [30] introduced dual-axis solar tracking for maximizing energy yield, whereas our system emphasizes ease of deployment and integration within a scalable IoST framework, making it suitable for widespread adoption in various settings. Overall, our proposed system distinguishes itself by providing a comprehensive solution for optimizing solar energy generation through seamless monitoring and tracking functionalities integration. The current system also proposes a novel approach to predict the abnormality in solar panel output, by which we may easily detect defective solar panels in a huge grid. Table 1 illustrates a comparison between existing systems and the novelty of the proposed system.

Table 1. Comparison between existing systems and new system.

Existing Systems	Novel Features and Enhancements
Mishra et al. (2020) [26]	Focused on IoT-based monitoring.
Haligaswatta et al. (2019) [27]	Explored solar tracking using fuzzy logic controllers.
Chen et al. (2018) [28]	Emphasized predictive analytics for optimization.
Khalil et al. (2017) [29]	Utilized Arduino and GPS modules for solar tracking.
Carrasco et al. (2016) [30]	Introduced dual-axis solar tracking for maximizing energy yield.
Mellit and Kalogirou (2021) [31]	Combined AI and IoT for enhanced diagnosis and remote sensing of solar PV systems.
Badave et al. (2018) [32]	Developed an IoT-based health monitoring system for solar PV panels.
Nath et al. (2023) [33]	Provided a comprehensive review on IoT integration with solar energy applications.
Mostofa and Islam (2023) [34]	Created an IoT system for live and remote monitoring of solar PV facilities.
AlMallahi et al. (2023) [35]	Conducted a bibliometric analysis and highlighted global publication trends in IoT and solar energy.
Proposed IoST-based System	Extends functionality to include solar tracking capabilities, integrating light-dependent sensors and servo motors for precise panel orientation. Offers real-time monitoring and tracking, scalability, and remote accessibility through cloud integration within a scalable IoST framework. Emphasizes ease of deployment and integration, making it suitable for widespread adoption in various settings. The current system also proposes a novel approach to predict the abnormality in solar panel output, by which we may easily detect defective solar panels in a huge grid.

3. Methodology

3.1. Hypothesis

The hypothesis posits that the integration of solar panel monitoring and sun-tracking mechanisms, facilitated by the Internet of Sensing Things (IoST) technology, will enhance solar energy system efficiency. This integration enables real-time data analysis and optimization of solar panel orientation to maximize power generation by aligning panels with the sun's position throughout the day. Furthermore, it is anticipated that the wattage data obtained from both tracked and non-tracked solar panels will follow the Rayleigh distribution. Deviations from this distribution will signal anomalies in the solar panel performance. By leveraging this statistical model and monitoring capabilities, maximum power gain can be achieved, leading to improved system reliability and maintenance strategies.

3.2. The Mathematical Background

In this work, several sensors have been used to measure temperature, current, voltage, and radiation. For measuring temperature, the LM35 temperature sensor (Made in China) is used, which can measure temperatures from $-55\text{ }^{\circ}\text{C}$ to $150\text{ }^{\circ}\text{C}$. After connecting the input pin to a regulated voltage of $+5\text{ V}$ and the ground pin to the circuit's ground,

the temperature can be measured. Equation (1) shows the calculation for measuring temperature, as follows:

$$V_{\text{out}} = 10 \text{ mV} \cdot T \quad (1)$$

where V_{out} is the LM35 output voltage and T is the temperature in °C. When the output voltage is 0 V, the temperature will be 0 °C, with an increase of 0.01 V (10 mV) for each degree of temperature increase. For example, at a temperature of −10 °C, the output voltage would be −100 mV. In our system, when the temperature falls below 0 °C, the system will not proceed to measure the voltage, since, for the systems considered in this article, the solar panels will not provide enough power at these low temperatures.

For measuring voltage and current, the ACS712 current sensor (made in China) is used. Equation (2) shows the calculation for voltage, as follows:

$$V_{\text{sensor}} = \frac{\text{RawValue}}{1024} \times 5000 \quad (2)$$

where V_{sensor} is the calculated voltage and RawValue is the analogRead value of the sensor. Equation (3) shows the calculation for current, as follows:

$$I_{\text{sensor}} = \frac{V_{\text{sensor}} - V_{\text{offset}}}{\text{mVperAmp}} \quad (3)$$

where I_{sensor} is the calculated current in amperes, V_{sensor} is the calculated voltage, V_{offset} is 2500 mV (since Arduino UNO operates at 5000 mV), and mVperAmp is 100 for a 20 A module and 66 for a 30 A module.

The resistance of the LDR differs according to the amount of light that falls on it. For resistance R_L and light intensity in Lux, the following is true:

$$R_L = \frac{500}{\text{Lux}} \quad (4)$$

The LDR is connected to +5 V of Arduino through a 3.3 k resistor. The output voltage V_0 will be as follows:

$$V_0 = 5 \times \frac{R_L}{R_L + 3.3} \quad (5)$$

From these two equations, we can obtain the light intensity as follows:

$$\text{Lux} = \frac{2500}{V_0 - 500} \div 3.3 \quad (6)$$

For monitoring system efficiency, we can formulate equations relating to the power gain with and without the solar tracker, considering factors such as solar radiation intensity, panel orientation, and tracking accuracy. These equations can involve integrals representing the area under the power curve over time, considering variations in solar radiation throughout the day and year.

To control a solar panel's angle using one servo motor and two light-dependent resistors (LDRs), we can utilize the difference in light intensities detected by the LDRs to determine the optimal angle for the solar panel. The aim is to keep the solar panel perpendicular to the direction of the sunlight, which is indicated by the balance of light intensities between the two LDRs.

Let I_1 and I_2 be the light intensities measured by the LDRs I_1 and I_2 , respectively. The servo motor will adjust the angle θ of the solar panel based on the difference between I_1 and I_2 . The angle θ can be calculated using the following equation:

$$\theta = K \cdot (I_1 - I_2) \quad (7)$$

In this equation, K is a proportional constant that converts the difference in light intensities into an angular displacement. The value of K depends on the sensitivity of the LDRs and the mechanical configuration of the servo motor. Essentially, K is a gain factor that ensures the servo motor responds appropriately to the detected light difference.

However, to ensure that the angle θ remains within the operational range of the servo motor, which is between 0 and 120 degrees, we need to constrain the calculated angle. This can be achieved using the max and min functions, which limit the angle to the desired range. The constrained equation for θ is as follows:

$$\theta = \min(\max(0, K \cdot (I_1 - I_2)), 120) \quad (8)$$

This equation ensures that if the calculated angle $K \cdot (I_1 - I_2)$ is less than 0, the angle is set to 0 degrees, and, if the calculated angle is greater than 120, the angle is set to 120 degrees. This way, the solar panel's angle is always within the range of 0 to 120 degrees.

In summary, the process involves measuring the light intensities I_1 and I_2 using the LDRs, calculating the difference between these intensities, and then adjusting the servo motor's angle θ accordingly. The final angle is constrained to ensure it stays within the operational limits of the servo motor. This method allows the solar panel to track the sun effectively by continuously adjusting its angle based on the light intensity difference detected by the two LDRs.

To calculate the system efficiency and power gain, we should deduct the power consumed by the tracking mechanism by the servo motor. The solar panel we will use has a 1.5 kg weight. The power needed to move the solar panel to track the sun's movement from 9 a.m. to 5 p.m., considering an 8 h duration, should be measured directly.

We assume the following:

- Moment of inertia $I = 0.5 \text{ kg/m}^2$;
- Angular acceleration $\alpha = \frac{\Delta\omega}{\Delta t}$;
- Time duration $\Delta t = 8 \text{ h} = 28,800 \text{ s}$ (assuming 3600 s per hour);
- Change in angular velocity $\Delta\omega = 120^\circ$.

First, let us calculate the angular acceleration as follows:

$$\alpha = \frac{\Delta\omega}{\Delta t} = \frac{120^\circ \times \frac{\pi}{180}}{8 \times 3600 \text{ s}} \approx 0.000043 \text{ rad/s}^2 \quad (9)$$

Now, we can calculate the torque using the following formula:

$$\tau = I \cdot \alpha = 0.5 \text{ kg/m}^2 \times 0.000043 \text{ rad/s}^2 \approx 0.0000215 \text{ Nm} \quad (10)$$

Finally, we can calculate the power needed using the following formula:

$$P = \tau \cdot \omega \quad (11)$$

We need to convert the angular velocity to radians per second, as follows:

$$\omega = \frac{120^\circ \times \frac{\pi}{180}}{8 \times 3600 \text{ s}} \approx 0.000043 \text{ rad/s} \quad (12)$$

Substituting this into the power formula gives the following:

$$P = 0.0000215 \text{ Nm} \times 0.000043 \text{ rad/s} \approx 9.245 \times 10^{-10} \text{ W} \quad (13)$$

Therefore, the power needed to move the solar panel to track the sun over 8 h is approximately $9.245 \times 10^{-10} \text{ W}$. We will subtract this power from our power gain.

The percentage increase in power gain for tracking solar panels compared to non-tracking panels will be calculated as follows:

$$PI = \frac{MPGT - MPGN - SPC}{MPGN} \times 100\% \quad (14)$$

where PI = percentage increase, MPGT = mean power gain (tracking), MPGN = mean power gain (non-tracking), and SPC = servo power consumption. The power consumption for the solar monitoring system will be deducted from both tracked and non-tracked panels where both will be canceled by each other, so the power gain increase calculation will not consider them.

3.3. Algorithm

The algorithm for the system (Algorithm 1) is unified into a cohesive process, incorporating both Arduino UNO and NodeMCU functionalities.

Algorithm 1 Solar Panel Monitoring and Tracking Algorithm

- 1: **Initialization Phase:**
 - 2: Include necessary libraries.
 - 3: Implement Arduino software serial for ESP8266.
 - 4: Declare variables: T , V , I , $ldr1value$, $ldr2value$.
 - 5: Establish serial communication between Arduino UNO and ESP8266.
 - 6: Connect NodeMCU to the Wi-Fi network.
 - 7: **Data Acquisition and Processing:**
 - 8: Read LM35 temperature sensor analog value: T_{analog} .
 - 9: Convert T_{analog} to temperature in Celsius: $T = T_{analog} \times 0.1$.
 - 10: Obtain voltage and current values from ACS712 Current Sensor: V , I .
 - 11: Read light intensity values from LDR sensors: $ldr1value$, $ldr2value$.
 - 12: Determine optimal solar panel orientation:
 - 13: **if** $ldr1value > ldr2value$ **then**
 - 14: Adjust solar panel orientation towards $ldr1$.
 - 15: **else**
 - 16: Adjust solar panel orientation towards $ldr2$.
 - 17: **end if**
 - 18: **Data Transmission and Monitoring:**
 - 19: Concatenate sensor values: $data = (T, V, I, ldr1value, ldr2value)$.
 - 20: Send $data$ to NodeMCU via serial communication.
 - 21: Upon receiving $data$, separate sensor values.
 - 22: Transmit sensor data to ThingSpeak cloud server for monitoring.
 - 23: Set ThingSpeak field values: Temperature, Light intensity, Voltage, Current.
 - 24: Write sensor data to specified ThingSpeak channel using Write API key.
 - 25: Implement a 15-s delay for regular updates on ThingSpeak.
-

Algorithm 1 is designed to adjust the solar panel orientation based on light intensity readings from LDR sensors. The process iteratively compares the values from two sensors ($ldr1value$ and $ldr2value$) and adjusts the panel orientation to maximize the light intensity; while this approach aims to find an optimal orientation, it may not always converge to the global optimum due to changing environmental conditions and the presence of local maxima. Future work will explore advanced optimization techniques to enhance convergence reliability.

3.4. System Architecture

The solar panel serves as the primary energy converter, harnessing solar radiation. Two microcontrollers are employed: Arduino UNO gathers sensor data and communicates it to NodeMCU via serial connection. NodeMCU then transmits the data to the Thingspeak cloud server. A servo motor facilitates solar panel alignment with the sun's movement. The

LM35 sensor measures real-time temperature, while a dependent sensor gauges sunlight intensity. Current and voltage measurements utilize ACS712 Current and Voltage sensors. Interconnections are established on a Breadboard using jumper wires. A lithium battery powers both microcontrollers.

The system flow of the solar panel monitoring system and the system flow of the solar panel tracking system are illustrated in Figure 4.

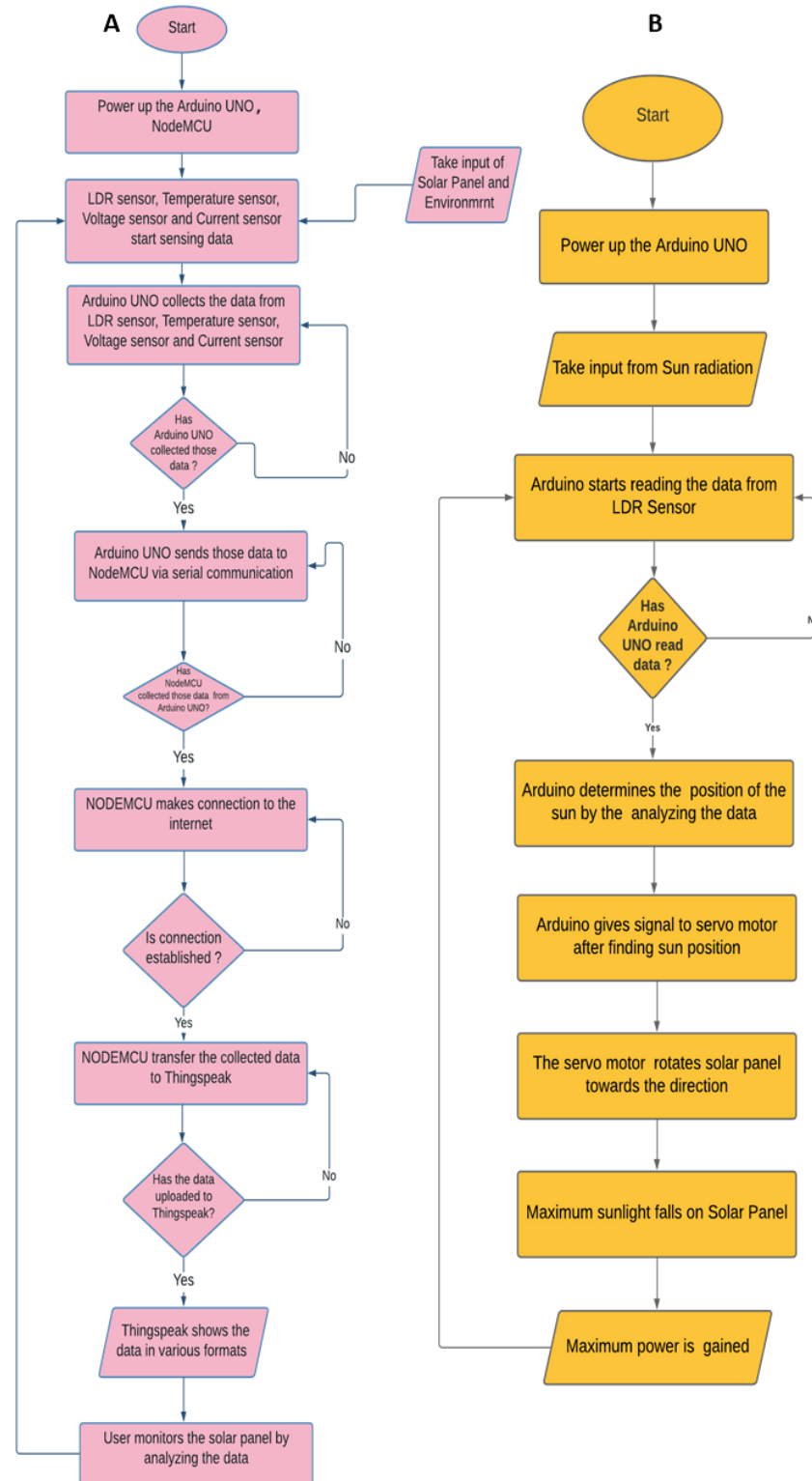


Figure 4. System flow: (A) solar panel monitoring and (B) solar panel tracking.

The primary circuit diagram of the IoST solar panel monitoring and tracking system is depicted in Figure 5. The prototype incorporates an OLED Display, DHT11 temperature and humidity sensor, ACS712 current sensor, ESP8266 Wi-Fi module, Arduino UNO R3, MG995 Servo motor, 1 k and 10 k ohm resistors for voltage measurement, and three LDR sensors (two for sun tracking and one for light intensity measurement). All these pieces of equipment are made in China. Data are transmitted to the ThingSpeak platform for analysis, visualization, and additional data processing.

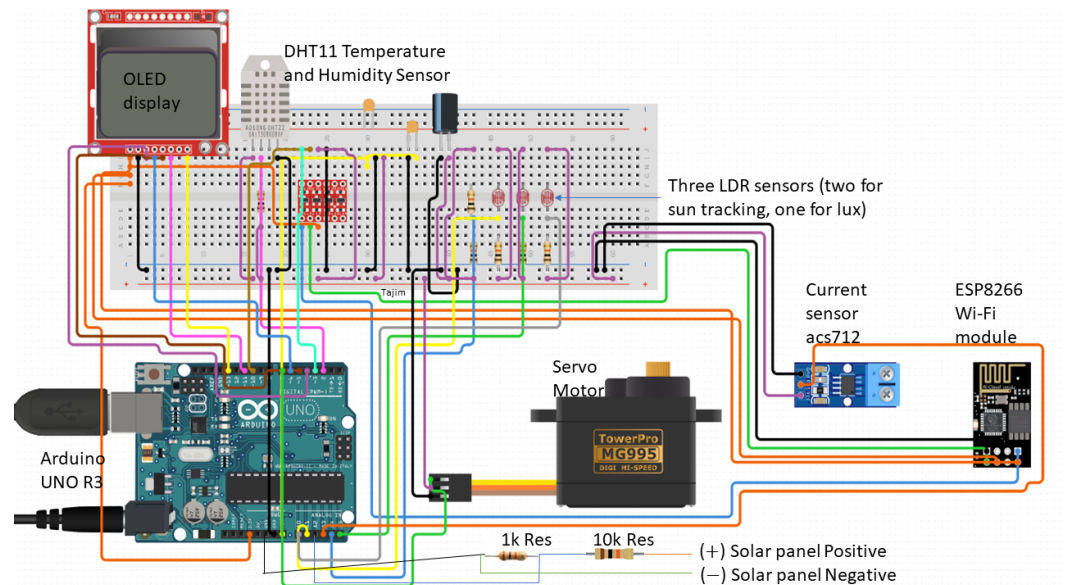


Figure 5. Circuit diagram of IoST solar panel monitoring and tracking system.

3.5. Anomaly Prediction in Solar Panel with IoST Monitoring

Anomaly prediction in solar panel systems is crucial for identifying potential malfunctions or deviations from expected performance. By leveraging IoST monitoring data, we can employ statistical distribution analysis to predict anomalies in solar panel wattage readings.

3.5.1. Statistical Distribution Analysis

First, we perform a statistical distribution analysis to identify the distribution that best fits the observed wattage data. Among various candidate distributions, including Normal, Exponential, Logistic, Gumbel (Right), Gumbel (Left), Gamma, Lognormal, Rayleigh, Laplace, Beta, Chi-Squared, Pareto, and Uniform, we select the Rayleigh distribution as the most suitable model for our data.

The Kolmogorov–Smirnov (KS) statistic is utilized to quantify the goodness-of-fit for each distribution. The KS statistic measures the maximum difference between the empirical cumulative distribution function (CDF) of the observed data and the theoretical CDF of the selected distribution.

3.5.2. Probability Density Estimation

The wattage distribution refers to the statistical representation of the power output (in watts) from the solar panels over a given period. In the context of the Rayleigh distribution, the probability density function (PDF) describes how the power output values are distributed. The Rayleigh distribution's PDF is given by the following equation:

$$f(x; \sigma) = \frac{x}{\sigma^2} e^{-\frac{x^2}{2\sigma^2}} \quad (15)$$

where x represents the wattage value (the power output from the solar panels) and σ is the scale parameter estimated from the data. The wattage distribution, therefore, is the

distribution of these wattage values modeled by the Rayleigh distribution, helping to understand the typical power generation behavior and identifying deviations that may indicate anomalies.

The scale parameter (σ) in the Rayleigh distribution can be calculated using the maximum likelihood estimation (MLE) method. For a given set of wattage data $\{x_1, x_2, \dots, x_n\}$, the scale parameter σ is estimated as follows:

$$\sigma = \sqrt{\frac{1}{2n} \sum_{i=1}^n x_i^2} \quad (16)$$

where x_i represents individual wattage readings and n is the number of observations.

3.5.3. Threshold Selection

To detect anomalies, we establish a threshold based on the PDF of the Rayleigh distribution. This threshold is typically set at a predefined significance level, such as the 95th percentile of the distribution, indicating values that are unlikely to occur under normal conditions.

3.5.4. Anomaly Detection

For each wattage observation in the dataset, we calculate its probability density under the Rayleigh distribution. If the probability density falls below the established threshold, the observation is flagged as an anomaly.

3.5.5. Visualization and Reporting

Anomalies are visualized on a plot alongside the original wattage data points, facilitating easy identification and interpretation. Additionally, a comprehensive report is generated, summarizing the detected anomalies and their corresponding timestamps for further analysis and action.

3.5.6. Refinement and Validation

The anomaly detection process is refined and validated through comparison with known anomalies or by conducting additional analyses. Adjustments to the threshold or distribution selection may be made to enhance the accuracy and reliability of anomaly prediction.

4. Experimental Results

4.1. Output and Features

The solar panel tracking system consists of Arduino UNO, two LDR sensors, jumper wires, a solar panel, a USB cable, and a servo motor. Sun radiation is detected by the solar panel, and the two LDR sensors measure the radiation intensity. Based on these readings, Arduino UNO controls the servo motor, ensuring that the solar panel rotates toward the direction of maximum sunlight exposure. Users can access real-time data through various graphs and widgets provided by the Thingspeak platform. Additionally, data can be exported in different formats, facilitating comprehensive monitoring of solar panels. Figure 6 demonstrates the monitoring of solar panels and the associated measurements on laptops and mobile devices using the Thingspeak Server. NodeMCU establishes an internet connection to transmit data to the cloud server “Thingspeak”. Thingspeak offers a variety of visualization methods and exporting features for comprehensive data analysis.

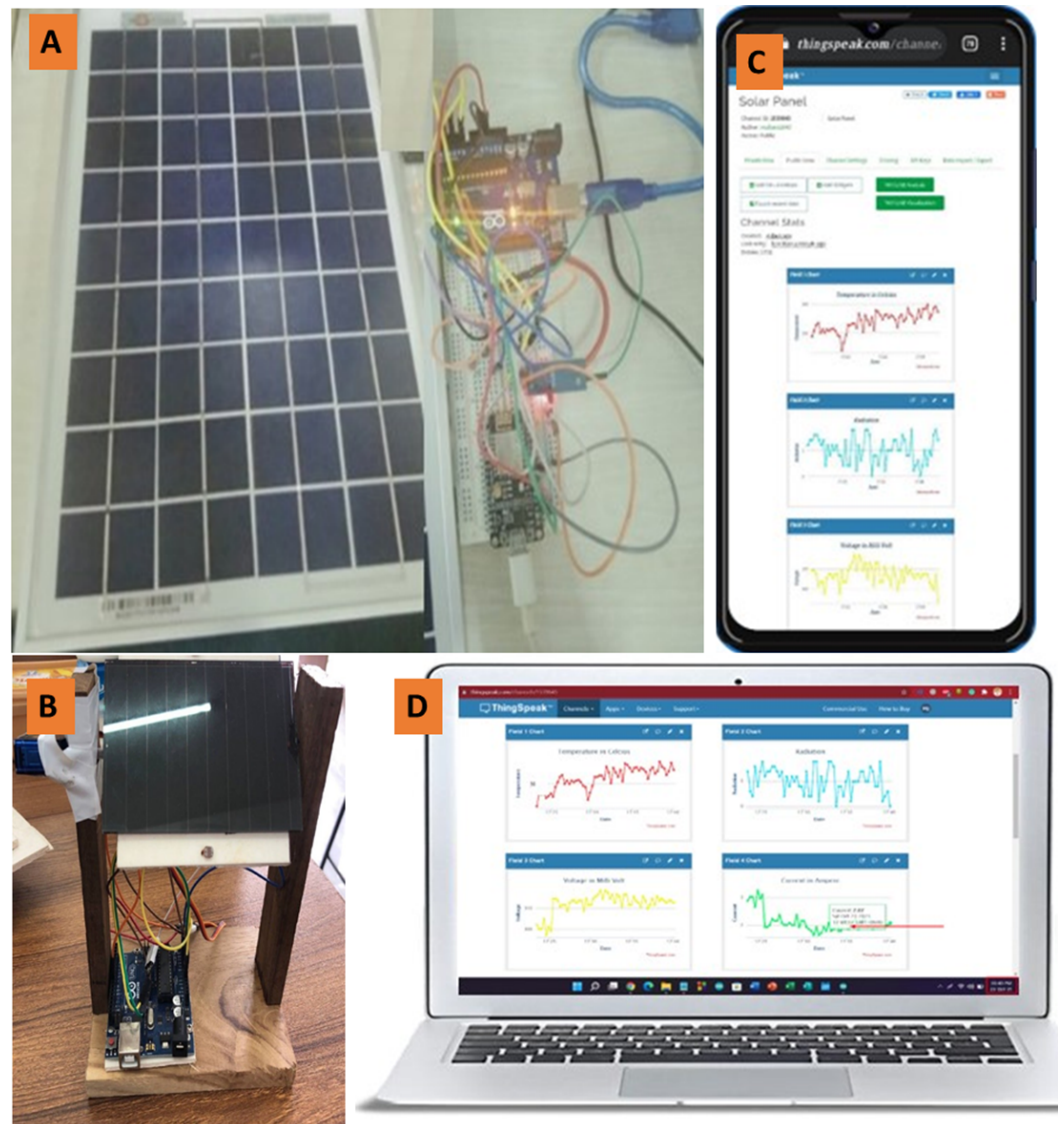


Figure 6. Output of (A) solar panel monitoring system, (B) miniature prototype of the solar tracking system, (C) real-time visualization on Thingspeak channel from a laptop, and (D) real-time visualization on Thingspeak channel from a smartphone.

The system exhibits the following features:

- **Temperature sensing:** the LM35 temperature sensor accurately senses the environment's temperature, providing data with a reliability of 96% among 1000 tests.
- **LDR sensing:** LDR sensors effectively detect areas of maximum sunlight, aiding in optimal solar panel orientation with an accuracy rate of 97% among 1000 tests.
- **Servo motor movement:** The servo motor, guided by LDR data, ensures the solar panel is oriented towards maximum sunlight. It exhibits consistent movement in alignment with the sun's radiation, achieving a reliability of 98% among 1000 tests.
- **Current and voltage sensing:** Voltage and current sensing achieve a remarkable 97% accuracy rate, ensuring precise monitoring of solar panel performance. Extensive testing, comprising 1000 trials, confirms the reliability of these sensors. Data integrity on the ThingSpeak server remains consistently high at 97%, complemented by 98% accuracy in graphical representations. This rigorous testing underscores our commitment to delivering accurate results vital for effective solar panel management.
- **Solar tracker performance:** the solar panel tracking system accurately aligned with the sun's position in 99% of 1000 tests, highlighting its reliability and effectiveness.

- Cloud monitoring: the monitoring system from cloud server ThingSpeak worked successfully.

4.2. Experimental Results

To evaluate the performance of the solar panel monitoring system, an experiment was conducted over twenty days in Dhaka, Bangladesh, in March 2023. The experiment involved deploying two sets of solar panels: one with solar tracking capabilities and the other without. Each set consisted of five monocrystalline solar panels rated at 25 W and 12 V.

4.2.1. Experimental Setup

- *Tracked solar panels:* These panels were equipped with solar-tracking mechanisms to continuously adjust their orientation for optimal sunlight exposure throughout the day. Solar tracking is single-axis sun tracking.
- *Non-tracked solar panels:* These panels remained fixed in position without solar-tracking capabilities.

4.2.2. Data Collection

- Data collection occurred from 9:00 AM to 5:00 PM each day.
- Measurements were taken at 5 min intervals.
- Each dataset included the following parameters: temperature (°C), humidity (%), voltage (V), current (A), lux (lux), and power gain (W).

This experimental setup allowed for a comprehensive assessment of the proposed solar panel monitoring system's efficacy in optimizing power gain, particularly in the context of solar-tracking functionality.

4.2.3. Obtained Dataset Description

The dataset comprises measurements collected from both tracking and non-tracking solar panels over three days. Each dataset includes metrics such as temperature (°C), humidity (%), voltage (V), current (A), lux, and power gain (W). The measurements were recorded every 5 min from 9:00 AM to 5:00 PM.

4.2.4. Results Analysis

The statistical comparison between tracking and non-tracking solar panels reveals notable differences in various metrics illustrated in Table 2. Notably, the mean power gain for tracking solar panels is higher compared to non-tracking panels, indicating the effectiveness of solar panel tracking in maximizing energy production.

Table 2. Statistical comparison between tracking and non-tracking solar panels.

Metric	Tracking Solar Panels	Non-Tracking Solar Panels
Mean temperature (°C)	23.06	23.06
Mean humidity (%)	49.56	49.56
Mean voltage (V)	7.07	5.73
Mean current (A)	1.25	1.00
Mean lux	27,261.89	25,360.14
Mean power gain (W)	8.79	7.02
Median temperature (°C)	22.90	22.90
Median humidity (%)	50.00	50.00
Median voltage (V)	7.15	5.25
Median current (A)	1.24	0.95
Median lux	19,451.00	17,773.00
Median power gain (W)	8.06	5.90

Using the calculated values and Equation (14), we find the following:

For tracking solar panels: MPG = 8.79 W.

From Equation (13) for tracking solar panels: SPC = 9.245×10^{-10} .

For non-tracking solar panels: MPN = 7.02 W.

Finally, the power gain increase can be calculated as follows:

$$\begin{aligned} \text{PI} &= \frac{8.79 - 7.02 - 9.245 \times 10^{-10}}{7.02} \times 100\% \\ &\approx \frac{1.7679 - 0.0000009245}{7.02} \times 100\% \approx 25.17\% \end{aligned} \quad (17)$$

Therefore, with the results, we can see an increase of 25.17% power gain with the proposed system. Figure 7 shows the statistical comparison of the system results. The results demonstrate a significant improvement in power gain with solar panel tracking, highlighting its importance in enhancing solar energy generation efficiency.

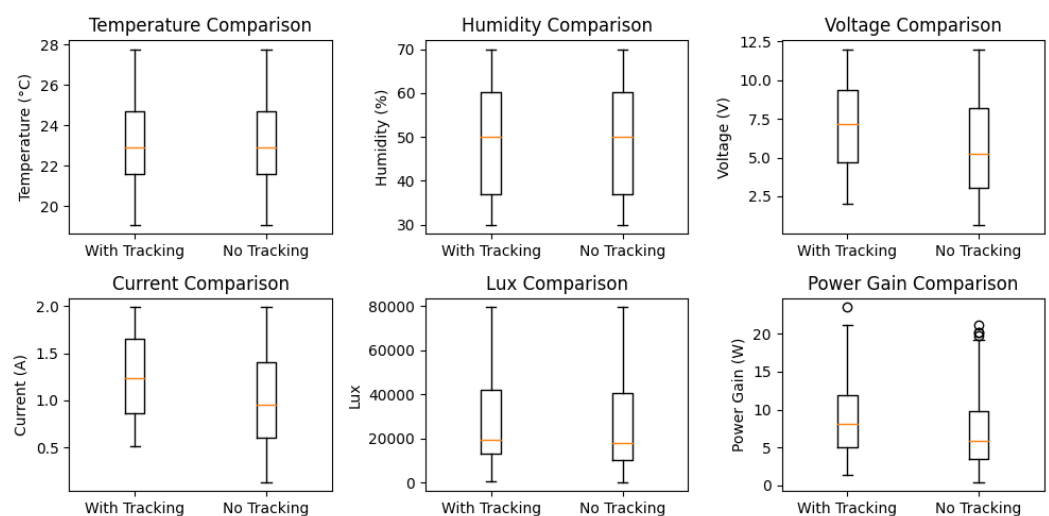


Figure 7. Statistical comparison of the system results.

4.3. Anomaly Prediction in Solar Panels with IoST Monitoring Results

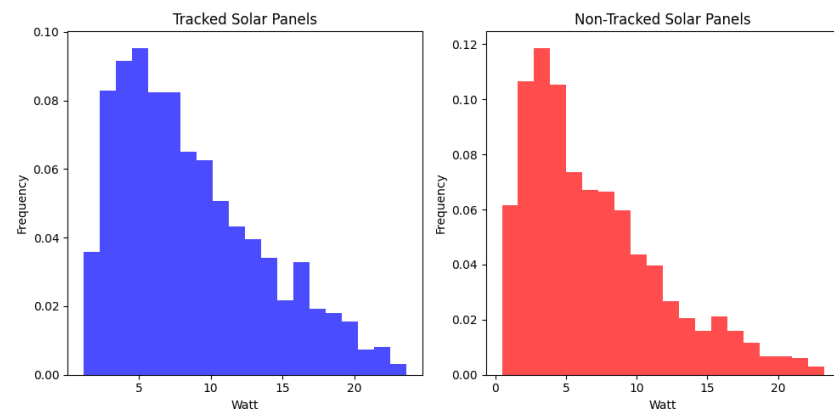
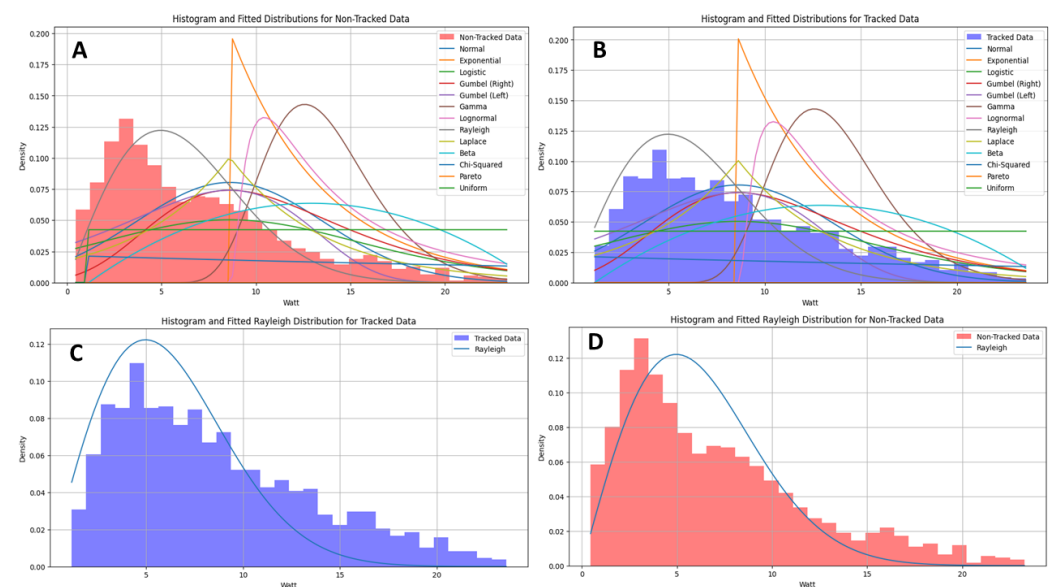
Table 3 illustrates the Kolmogorov–Smirnov (KS) statistic for various candidate distributions fitted to the tracked and non-tracked data. The KS statistic quantifies the goodness-of-fit of each distribution to the observed wattage data. The lower the KS statistic, the better the fit of the distribution to the observed data. Thus, the Rayleigh distribution appears to be the most appropriate model for representing the wattage distribution of solar panels in both tracked and non-tracked scenarios.

Figure 8 illustrates the histogram of the obtained watts from the tracked (left) and non-tracked (right) solar panels. The results of anomaly prediction in solar panels using IoST monitoring data are presented below, along with the comparison of distributions for tracked and non-tracked data.

Figure 9 presents four subfigures (A, B, C, D) displaying histograms and fitted distributions for both tracked and non-tracked data. Subfigures A and B show histograms with 13 different distributions overlaid for tracked and non-tracked data, respectively. Subfigures C and D specifically highlight the Rayleigh distribution overlaid on the histograms for tracked and non-tracked data, respectively. The Rayleigh distribution closely fits the observed wattage data in both cases, suggesting its adequacy for representing solar panel wattage distributions. Anomalies can be discerned by comparing actual wattage readings against a threshold established based on the Rayleigh distribution.

Table 3. Comparison of distributions for tracked and non-tracked data.

Distributions	Tracked Data KS Statistic	Non-Tracked Data KS Statistic
Normal	0.094	0.248
Exponential	0.578	0.691
Logistic	0.178	0.201
Gumbel (Right)	0.228	0.361
Gumbel (Left)	0.192	0.197
Gamma	0.584	0.692
Lognormal	0.601	0.715
Rayleigh	0.210	0.117
Laplace	0.119	0.240
Beta	0.351	0.458
Chi-Squared	0.642	0.645
Pareto	1.000	1.000
Uniform	0.303	0.422

**Figure 8.** Histogram of the obtained watts from the tracked (left) and non-tracked (right) solar panels.**Figure 9.** Histogram and fitted distributions for tracked and non-tracked data ((A): 13 distributions with tracked data, (B): 13 distributions with non-tracked data, (C): Rayleigh distribution with tracked data, (D): Rayleigh distribution with non-tracked data).

Anomalies in solar panels can be predicted using the fitted Rayleigh distribution. By establishing a threshold based on the Rayleigh distribution, wattage readings that deviate

significantly from the expected distribution can be flagged as anomalies. For example, wattage readings falling beyond a certain standard deviation from the mean of the Rayleigh distribution may indicate potential anomalies, such as malfunctioning solar panels or environmental disturbances affecting energy production. To predict anomalies, compare observed wattage readings with the expected distribution modeled by the Rayleigh distribution. If the observed wattage falls outside a predefined threshold, it can be classified as an anomaly, warranting further investigation or maintenance.

Using table to determine best fit: Table 3 compares the Kolmogorov–Smirnov (KS) statistics for various distributions fitted to the wattage data. The distribution with the lowest KS statistic indicates the best fit to the observed data. In our analysis, the Rayleigh distribution consistently showed the lowest KS statistic for both tracked and non-tracked data, suggesting it is the most appropriate model for our dataset. This result is dataset-dependent, and the best-fit distribution may vary with different datasets. However, given the robustness of our dataset, we can confidently generalize our findings to solar panels with similar setups, enhancing the reliability and applicability of our anomaly detection method.

Setting the anomaly threshold: The anomaly threshold is established based on the PDF of the Rayleigh distribution. Typically, this threshold is set at a predefined significance level, such as the 95th percentile, indicating that values beyond this point are considered anomalies. The threshold can be dynamically adjusted based on various factors, including temperature, humidity, and overall wattage distribution. For example, higher temperatures or unusual humidity levels may necessitate a lower threshold to account for their impact on solar panel performance.

5. Discussion

5.1. Optimizing Power Gain with Solar Panel Monitoring in Large-Scale Plants

Leveraging solar panel monitoring systems is crucial for maximizing power gain in large-scale solar plants. A synthesis of how solar panel monitoring can augment power gain in large-scale solar power plants includes the following:

- Real-time performance monitoring: the continuous monitoring of temperature, voltage, current, and sunlight intensity enables the immediate detection of underperforming panels or subsystems.
- Early issue detection: the prompt identification of performance issues allows for timely interventions, such as cleaning, maintenance, or repair, minimizing downtime and maximizing energy production.
- Advanced analytics: the integration of predictive algorithms offers insights into performance trends and patterns, enabling operators to optimize energy capture based on weather conditions and environmental factors.
- Holistic management: solar panel monitoring systems facilitate coordinated adjustments in panel orientation, tilt angles, and tracking mechanisms to optimize energy capture throughout the day and across seasons.
- Scalability and remote accessibility: centralized monitoring platforms streamline oversight of multiple solar installations spanning vast geographical areas from a single dashboard, facilitating proactive decision-making.
- Anomaly detection: the present system introduces an innovative method for anticipating anomalies in solar panel output, facilitating the swift identification of malfunctioning solar panels within expansive grids.

In essence, solar panel monitoring systems provide a proactive and automated approach to optimizing the performance of large-scale solar power plants, thereby increasing power gain and unlocking the full potential of solar energy as a clean, sustainable, and economically viable power source.

5.2. Hypothesis Validation

The experimental results offer compelling evidence supporting our hypothesis regarding the effectiveness of the proposed solar panel monitoring and tracking system. The

statistical analysis demonstrates significant improvements across various metrics between the tracking and non-tracking solar panels. Particularly noteworthy is the substantial increase in mean power gain observed for the tracking solar panels compared to their non-tracking counterparts, indicative of the system's capacity to optimize energy production. This enhancement in power gain is consistently echoed in the median power gain results, further affirming the superiority of tracking panels. Moreover, accounting for factors such as servo power consumption, the percentage increase in power gain reinforces the system's ability to enhance solar energy generation efficiency. These results underscore the efficacy of the Internet of Sensing Things-driven monitoring and sun-tracking technology in advancing solar energy systems, aligning closely with our initial hypothesis. Additionally, the statistical comparison presented in Figure 7, Table 2, and Equation (17) provides both visual and quantitative evidence of the system's performance, offering comprehensive validation of our hypothesis. Furthermore, the histogram and fitted distributions presented in Figure 9 highlight the distributional characteristics of the tracked and non-tracked data, emphasizing the suitability of the Rayleigh distribution for modeling solar panel wattage distributions and identifying anomalies. Figure 9 also shows that tracked solar panels obtained watts are more similar to the Rayleigh distribution. Deviation from Rayleigh distribution will be a candidate for anomalies in power gain.

5.3. Limitations

The identified limitations of the system include the risk of component damage on rainy days without waterproof casing and reduced power generation capability in cloudy and foggy weather conditions. Proper maintenance will play a vital role in this system.

5.4. Obtained Features

The proposed system offers solutions to the following various societal challenges:

- Accessibility to electricity for underserved populations, contributing to poverty alleviation.
- Enhanced educational opportunities, enabling nighttime studying in rural areas.
- Improved agricultural practices through access to electricity for irrigation.
- Mitigation of flood-related challenges by providing electricity in affected areas through elevated solar panel installations.
- Broad applicability in educational, commercial, and residential settings, contributing to energy sustainability and cost savings.

6. Conclusions

This study presents a comprehensive and cost-effective Internet of Sensing Things (IoST)-driven monitoring system tailored for solar panels, augmented with advanced solar tracking functionality. Through the integration of cutting-edge sensors, microcontrollers, and cloud-based data storage, the system enables the real-time monitoring and optimization of solar panel performance, contributing to the efficient utilization of solar energy resources. The statistical analysis showcased the system's effectiveness in various parameters, including temperature sensing, light-dependent resistor (LDR)-based solar tracking, current generation, and voltage measurement. Particularly noteworthy is the significant enhancement in power gain facilitated by the inclusion of a solar tracker, underscoring the system's potential for maximizing energy output.

In future research, endeavors could focus on several areas for further improvement and innovation. Enhanced weather resistance measures, such as robust waterproof casing solutions, could be developed to ensure the protection of system components during adverse weather conditions, thereby increasing the system's reliability. Moreover, the integration of artificial intelligence algorithms, particularly for anomaly prediction using Rayleigh distribution, presents a promising avenue for optimizing system performance. By identifying irregularities in solar panel performance, predictive maintenance and fault detection can be facilitated, contributing to enhanced system reliability and longevity.

This research contributes to the advancement of efficient and sustainable solar energy systems. The integration of state-of-the-art technologies ensures the reliability and effectiveness of the proposed monitoring and tracking solution, thereby paving the way for enhanced performance and widespread adoption of solar energy.

Author Contributions: Conceptualization, T.M.N.U.A.; data curation, N.T.N. and M.W.; formal analysis, T.M.N.U.A. and M.A.J.; funding acquisition, M.W.; methodology, T.M.N.U.A., N.T.N. and M.A.J.; project administration, and M.W.; resources, N.T.N. and T.A.; software, T.M.N.U.A., M.A.J. and T.A.; supervision, M.W.; validation, T.M.N.U.A. and M.A.J.; visualization, T.A. and M.W.; writing—original draft, T.M.N.U.A. and N.T.N.; writing—review and editing, M.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ansari, S.; Ayob, A.; Lipu, M.S.H.; Saad, M.H.M.; Hussain, A. A Review of Monitoring Technologies for Solar PV Systems Using Data Processing Modules and Transmission Protocols: Progress, Challenges and Prospects. *Sustainability* **2021**, *13*, 8120. [\[CrossRef\]](#)
2. 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. [\[CrossRef\]](#)
3. Chowdhury, A.; Rahman, R. Design and implementation of a wireless sensor network for solar panel monitoring. *Sensors* **2018**, *18*, 145.
4. Huuhtanen, T.; Jung, A. Predictive maintenance of photovoltaic panels via deep learning. In *2018 IEEE Data Science Workshop (DSW)*; IEEE: New York, NY, USA, 2018; pp. 66–70.
5. Kaur, J.; Kaur, S. Development of mobile application for solar panel monitoring. *Int. J. Renew. Energy Res.* **2020**, *10*, 1234–1242.
6. 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)*, Bhopal, India, 27–29 October 2017; IEEE: New York, NY, USA, 2018; pp. 619–623.
7. Akhund, T.M.N.U.; Shaikh, Z.A.; De La Torre Díez, I.; Gafar, M.; Ajabani, D.H.; Alfarraj, O.; Tolba, A.; Fabian-Gongora, H.; López, L.A.D. IoST-Enabled Robotic Arm Control and Abnormality Prediction Using Minimal Flex Sensors and Gaussian Mixture Models. *IEEE Access* **2024**, *12*, 45265–45278. [\[CrossRef\]](#)
8. 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: New York, NY, USA, 2016; pp. 432–436.
9. 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. [\[CrossRef\]](#)
10. Akhund, T.M.N.U.; Hossain, M.; Kubra, K.; Nurjahan; Barros, A.; Whaiduzzaman, M. IoT based Low-cost Posture and Bluetooth Controlled Robot for Disabled and Virus Affected People. *Int. J. Adv. Comput. Sci. Appl.* **2022**, *13*, 691–700. [\[CrossRef\]](#)
11. Faridul Islam Suny, M.; Monjourur Roshed Fahim, M.; Rahman, M.; Newaz, N.T.; Akhund, T.M.N.U. IoT Past, Present, and Future a Literary Survey. *Lect. Notes Netw. Syst.* **2021**, *190*, 393–402.
12. Newaz, N.; Akhund, T.; Sarker, M.M. Internet of Things Based Low-Cost Health Screening and Mask Recognition System. *Int. J. Comput. Digit. Syst.* **2024**, *15*, 259–269. [\[CrossRef\]](#)
13. Priharti, W.; Rosmawati, A.F.K.; Wibawa, I.P.D. IoT Based Photovoltaic Monitoring System Application. *J. Phys. Conf. Ser.* **2019**, *1367*, 012069. [\[CrossRef\]](#)
14. Akhund, T.M.N.U.; Al-Nuwaiser, W.M. Human IoT Interaction Approach for Modeling Human Walking Patterns Using Two-Dimensional Levy Walk Distribution. *Int. J. Adv. Comput. Sci. Appl.* **2024**, *15*, 1514–1523. [\[CrossRef\]](#)
15. Phung, M.D.; Villefromoy, M.D.L.; Ha, Q. Management of Solar Energy in Microgrids Using IoT-Based Dependable Control. In *Proceedings of the 2017 20th International Conference on Electrical Machines and Systems (ICEMS)*, Sydney, NSW, Australia, 11–14 August 2017; IEEE: New York, NY, USA, 2017; pp. 1–6.
16. Rao, A.; Kumar, S.S. Smart IoT based solar panel cleaning system. In *Proceedings of the 2018 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, Bangalore, India, 18–19 May 2018; IEEE: New York, NY, USA, 2020; pp. 2357–2361.

17. Deenadayalan, K.D.; Arunraja, A.; Jayanthi, 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: New York, NY, USA, 2020; pp. 1009–1014.
18. Priyadharsini, K.; Dinesh Kumar, J.R.; Srikanth, A.; Sounddar, V.; Senthamilselvan, M. Elegant method to improve the efficiency of remotely located solar panels using IoT. *Mater. Today Proc.* **2021**, *45*, 8094–8104.
19. Trung, P.M.; Mariappan, V.; Cha, J.S. A study on IoT/LPWA-based low power solar panel monitoring system for smart city. *J. Korea Inst. Intell. Transp. Syst.* **2019**, *18*, 74–82. [[CrossRef](#)]
20. Ramu, S.K.; Irudayaraj, G.C.R.; Elango, R. An IoT-based smart monitoring scheme for solar PV applications. In *Electrical and Electronic Devices, Circuits, and Materials*; Wiley: Hoboken, NJ, USA, 2021; pp. 211–233.
21. Tellawar, M.P.; Chamat, N. An IOT based smart solar photovoltaic remote monitoring system. *Int. J. Eng. Res. Technol.* **2019**, *8*, 235–240.
22. Karthik, S.; Mahalakshmi, M.; Mahitha, R.; Meena, S. IoT Based Solar Panel Fault Monitoring and Control. *Int. J. Inf. Comput. Sci.* **2019**, *8*, 238–243.
23. Kavitha, V.; Malathi, V. A Smart Solar PV Monitoring System Using IoT. In Proceedings of the CS & IT Conference Proceedings, Wuhan, China, 12–13 July 2019; Volume 9.
24. Akon, H. IoT Based Weather Monitoring System with SMS Notification for DIU. Technical Report. 2020. Available online: <http://dspace.daffodilvarsity.edu.bd:8080/handle/123456789/4817> (accessed on 12 December 2023)
25. Akhund, T.M.N.U.; Newaz, N.T.; Rakib Hossain, M.; Shamim Kaiser, M. Low-Cost Smartphone-Controlled Remote Sensing IoT Robot. In *Information and Communication Technology for Competitive Strategies (ICTCS 2020)*; Kaiser, M.S., Xie, J., Rathore, V.S., Eds.; Springer: Singapore, 2021; pp. 569–576.
26. Mishra, A.; Singh, A.; Singh, S.; Kumar, S. IoT-based solar panel monitoring and optimization. In Proceedings of the 2020 IEEE 10th International Conference on Intelligent Systems and Control (ISCO), Varna, Bulgaria, 28–30 August 2020; IEEE: New York, NY, USA, 2020; pp. 1–5.
27. Haligaswatta, D.H.; Dahanayake, A.; Perera, I. Fuzzy logic-based solar tracking for photovoltaic systems. In Proceedings of the 2019 Moratuwa Engineering Research Conference (MERCon), Moratuwa, Sri Lanka, 3–5 July 2019; IEEE: New York, NY, USA, 2019; pp. 1–6.
28. Chen, C.; Zhou, G.; Zhang, W.; Wang, X. Predictive maintenance of solar panels using big data analytics. In Proceedings of the 2018 37th Chinese Control Conference (CCC), Wuhan, China, 25–27 July 2018; IEEE: New York, NY, USA, 2018; pp. 9048–9053.
29. Khalil, A.M.; Habib, A.F.; Alhassan, M. IoT based smart solar tracking system. In Proceedings of the 2017 8th International Renewable Energy Congress (IREC), Amman, Jordan, 21–23 March 2017; IEEE: New York, NY, USA, 2017; pp. 1–5.
30. Carrasco, J.M.; Galindo, J.L.; Manzano-Agugliaro, F.; Herrera-Viedma, E. A review of photovoltaic systems. *Sustainability* **2016**, *8*, 252.
31. 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](#)]
32. Badave, P.M.; Karthikeyan, B.; Badave, S.M.; Mahajan, S.B.; Sanjeevikumar, P.; Gill, G.S. Health monitoring system of solar photovoltaic panel: An internet of things application. In *Advances in Smart Grid and Renewable Energy, Proceedings of the ETAERE-2016, Majhitar, Sikkim, 17–18 December 2016*; Springer: Singapore, 2018; pp. 347–355.
33. Nath, D.C.; Kundu, I.; Sharma, A.; Shivhare, P.; Afzal, A.; Soudagar, M.E.M.; Park, S.G. Internet of Things integrated with solar energy applications: A state-of-the-art review. In *Environment, Development and Sustainability*; Springer Nature: New York, NY, USA, 2023; pp. 1–56.
34. Mostofa, K.Z.; Islam, M.A. Creation of an Internet of Things (IoT) system for the live and remote monitoring of solar photovoltaic facilities. *Energy Rep.* **2023**, *9*, 422–427. [[CrossRef](#)]
35. AlMallahi, M.N.; Al Nassan, W.; Obaideen, K.; Yousef, B.A.; AlJaghoub, H.; Ramadan, O.H.; AlShabi, M. Internet of Things (IoT) in solar energy: A bibliometrics analysis and global publications trends. In Proceedings of the Energy Harvesting and Storage: Materials, Devices, and Applications XIII, Orlando, FL, USA, 2 May 2023; SPIE: Bellingham, WA, USA, 2023; Volume 12513, pp. 113–120.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.