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Intelligent Solar Panel Monitoring Using Machine Learning and Cloud-Based Predictive Analytics

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Abstract

The increasing global energy demand necessitates reliable and sustainable solutions, with solar photovoltaic (PV) technology emerging as a key carbon-neutral option. However, optimizing solar energy systems requires advanced monitoring and predictive analytics to enhance efficiency and ensure long-term performance. This study introduces an Internet of Things (IoT)-based solar energy monitoring system, integrating machine learning algorithms and cloud computing to enhance real-time performance assessment. The proposed system employs K-Means Clustering for condition classification, Support Vector Machine (SVM) for fault detection, Long Short-Term Memory (LSTM) for energy forecasting, Prophet for time-series predictions, and Isolation Forest for anomaly detection. The system was validated using a 125-watt photovoltaic module, monitoring temperature, solar radiation, voltage, and current. A Wi-Fi-enabled microcontroller collects data, which is processed through a cloud-based platform and visualized via the Blynk application. Experimental results demonstrate 94.2% energy prediction accuracy using LSTM, 89.7% fault classification accuracy with SVM, and 88.5% anomaly detection accuracy with Isolation Forest, confirming high reliability. The system's wireless tracking mechanism minimizes resource consumption, ensuring scalability and adaptability for commercial and industrial applications. The integration of IoT, machine learning, and cloud analytics provides a cost-effective and scalable approach for solar PV optimization. Future enhancements include deep learning models and reinforcement learning algorithms to improve energy forecasting, fault detection, and adaptive optimization, ensuring greater efficiency, resilience, and sustainability in solar energy management.

Keywords: Solar PV, Sensors, Microcontrollers, IoT, Process Innovation, Product Innovation Data Science, Machine Learning, Predictive Analytics, Renewable Energy, K-Means Clustering, Support Vector Machine (SVM)

1. Introduction

Power generation plays a crucial role in the economic growth of emerging nations. Rapid industrialization and commercial expansion have significantly escalated energy demand, necessitating the adoption of sustainable and renewable energy solutions. As a response, there has been an increasing focus on harnessing renewable energy sources to meet these demands while addressing environmental challenges such as ozone layer depletion and greenhouse gas emissions [1]. Solar energy has gained immense popularity due to its high efficiency, cost-effectiveness, ease of installation, and minimal maintenance requirements.

The integration of the Internet of Things (IoT) has further revolutionized renewable energy systems [2]. IoT technology enables seamless communication and real-time data exchange among interconnected devices via cloud-based platforms, enhancing operational efficiency and user accessibility. In the context of solar energy, key factors influencing photovoltaic (PV) panel efficiency include temperature, solar radiation, current, voltage, and luminosity

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[3]. Real-time solar monitoring systems are essential in analyzing these parameters, allowing for proactive adjustments to optimize PV performance and reliability. The increasing research focus on solar energy technologies has led to the development of advanced data-driven approaches. Traditional solar energy management relies on simple forecasting databases, often structured using platforms like MySQL, to collect raw data and generate energy predictions. However, with the advent of artificial intelligence (AI) and machine learning techniques, predictive analytics has improved the accuracy and reliability of solar energy forecasting, enabling real-time monitoring and automated fault detection [4].

Different methods have been explored to evaluate the effectiveness of solar PV systems. For instance, LABVIEW is widely used as a data acquisition tool for real-time performance monitoring [5]. This platform provides a robust framework for tracking solar panel efficiency by continuously collecting operational data. To further enhance monitoring capabilities, microcontroller-based systems have been introduced to analyze performance factors, comparing real-world data against standard operating conditions to identify necessary optimizations.

A cost-effective IoT-based solar panel tracking system has been developed to enhance visualization and improve system performance. This approach not only aids in fault detection but also facilitates predictive maintenance. For remote photovoltaic installations, a cloud-based monitoring system utilizing Raspberry Pi is recommended. Real-time monitoring tools, such as LABVIEW, are employed to analyze critical PV system parameters, particularly for fault diagnosis in solar plants. Additionally, smart monitoring systems integrating microcontrollers and LABVIEW optimize the efficiency of sun-tracking mechanisms.

The adoption of remote solar control and monitoring systems enhances decision-making by providing automated data collection, storage, alerts, and visualization. A PV monitoring system leveraging both wired and wireless networks transmits parameters to an online application for remote access. LABVIEW is utilized to develop an intuitive interface for continuous solar PV monitoring, while an Arduino microcontroller processes observed variables and transmits data to a centralized server for analysis. This real-time monitoring capability enhances PV panel performance by detecting and mitigating performance degradation.

Furthermore, a cost-effective and intelligent design is proposed to maximize PV panel efficiency. A smart controller incorporating the Home Energy Management (HEM) algorithm [6] prioritizes resource allocation, optimizing solar PV utilization for household energy management. This study introduces an advanced IoT-enabled real-time solar PV tracking system, leveraging data science techniques for improved forecasting, fault detection, and performance optimization. By integrating machine learning-based classification models such as K-Means Clustering and Support Vector Machine (SVM), the system can effectively categorize PV panel conditions, ensuring enhanced efficiency and reliability.

2. Literature Review

The application of IoT and data science in solar panel monitoring has gained significant attention in recent years. Various studies have explored the integration of sensor-based monitoring systems with cloud computing to enhance energy efficiency and system reliability. According to Aman et al. [1], IoT-enabled energy systems provide real-time insights into solar power generation, allowing users to make informed decisions regarding energy consumption and resource allocation.

Several research works highlight the importance of predictive analytics in optimizing solar PV performance. Li et al. [3] demonstrated that machine learning models, such as artificial neural networks (ANNs) and SVM, could improve the accuracy of solar energy predictions. Their study emphasized the significance of temperature, irradiance, and environmental conditions in determining PV efficiency.

Another key area of research focuses on anomaly detection and fault diagnosis in solar energy systems. Mohd Isham et al. [4] implemented a real-time monitoring framework using LABVIEW and microcontroller-based sensors to detect deviations from standard operating conditions. Their findings indicated that integrating IoT with advanced analytics enhances fault detection capabilities, reducing maintenance costs and downtime.

Moreover, studies by Rehman et al. [2] explored the role of big data analytics in renewable energy management. Their research emphasized that the integration of cloud-based platforms with IoT sensors enables large-scale data collection, which can be processed using clustering algorithms like K-Means to categorize system performance and detect anomalies.

Furthermore, advancements in smart energy management have led to the development of intelligent controllers for optimizing solar PV utilization. Previous study [6] proposed a HEM algorithm that prioritizes energy allocation based on real-time demand and supply conditions. This approach has been widely adopted in smart grid applications to enhance sustainability and operational efficiency.

In conclusion, the literature highlights the growing significance of IoT and data science in improving solar panel monitoring systems. By leveraging machine learning techniques such as K-Means clustering and SVM, along with real-time IoT data collection, modern solar PV monitoring solutions can achieve greater efficiency, predictive maintenance, and optimized energy usage.

3. Proposed Architecture

A real-time solar energy tracking system is proposed, utilizing a three-layer IoT architecture. The foundational layer integrates various components, including actuators, sensors, RFID, photographic equipment, and controllers, forming a hybrid sensing and processing framework. This layer facilitates the acquisition and preliminary processing of data [7]. The transport layer, utilizing protocols such as TCP and UDP, manages the transmission of data packets from the intermediary layer. The intermediary layer, positioned below the networking layer, serves as a gateway, enabling communication between lower-level components and the higher-level architecture. This layer supports both wireless and wired networks, including LAN, Bluetooth, Zigbee, 4G, and Wi-Fi, ensuring seamless connectivity [8].

The system's final stages involve the use of a cloud platform for remote management and data storage, along with the application layer, which provides a graphical user interface (GUI) for end-users. This comprehensive architecture ensures efficient data collection, processing, and management, facilitating the real-time monitoring and optimization of solar energy systems [9]. Figure 1 illustrates the block diagram of the IoT-based solar monitoring system.

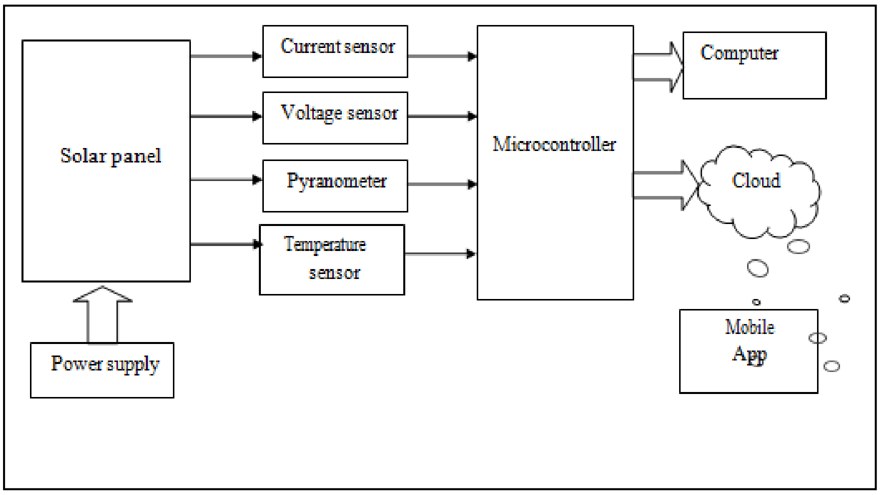

Figure 1. Block diagram for Internet of Things-based solar monitoring.

The system incorporates a 125-watt polycrystalline silicon solar panel as its primary energy-harvesting component. Voltage and current sensors are employed to measure the electrical parameters generated by the panel, providing real-time data on its operational status [10]. A temperature sensor is integrated directly onto the solar PV module to monitor surface temperatures, a parameter significantly impacting the efficiency of the solar panel. Additionally, a pyranometer is used to measure solar irradiance on a horizontal surface, expressed in watts per square meter (W/m^2), offering critical insights into the solar energy potential at the installation site [11].

A microcontroller serves as the central processing unit of the system, processing the data collected from these sensors. It facilitates real-time decision-making and data transmission to the cloud network through a wireless communication module, thereby enabling remote monitoring and optimization of the solar energy system. This integrated approach ensures comprehensive tracking and efficient management of the solar panel's performance [12].

3.1. Bottom Layer

The sensing components of the system include the ACS 712 current sensor, a voltage detector, a pyranometer, and a temperature sensor. Voltage reduction is measured using a voltage divider circuit, which employs series resistances as a voltage sensor. This circuit is particularly effective for detecting voltages exceeding five volts. The voltage is calculated using the resistance factor and a reference voltage. The schematic of the voltage divider circuit is presented in figure 2 [13].

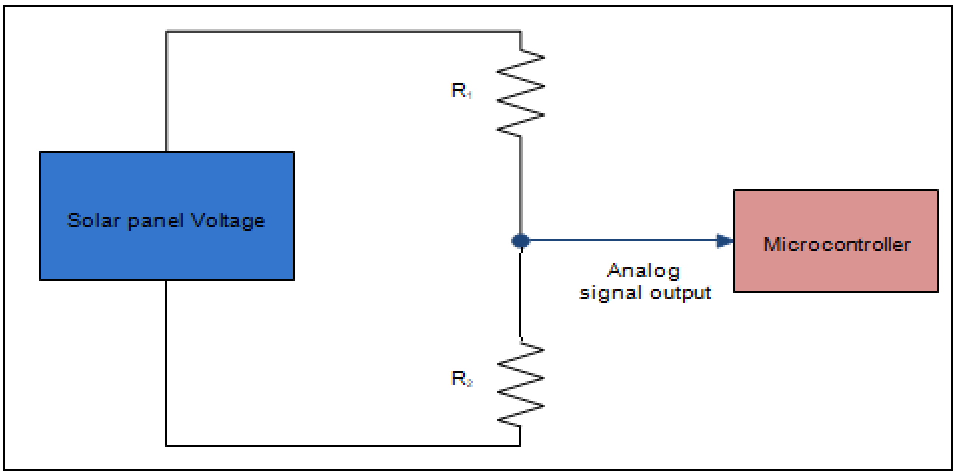

Figure 2. Voltage Divider Circuit

The formula used for calculating voltage is as follows:

$$Voltage = \left(\frac{Analog\ value}{Resistance\ Factor}\right) \times Reference\ Voltage \quad (1)$$

The resistance factor is determined based on the values of the series resistances R1 and R2. Solar PV panel current is measured using the ACS 712 Hall Effect current sensor, capable of detecting up to 20 Amperes. This technique can measure both DC and AC currents. The Hall Effect sensor connects to the microcontroller via three terminals: power supply, ground, and analog input. A schematic layout of the current sensor module is shown in figure 3 [14].

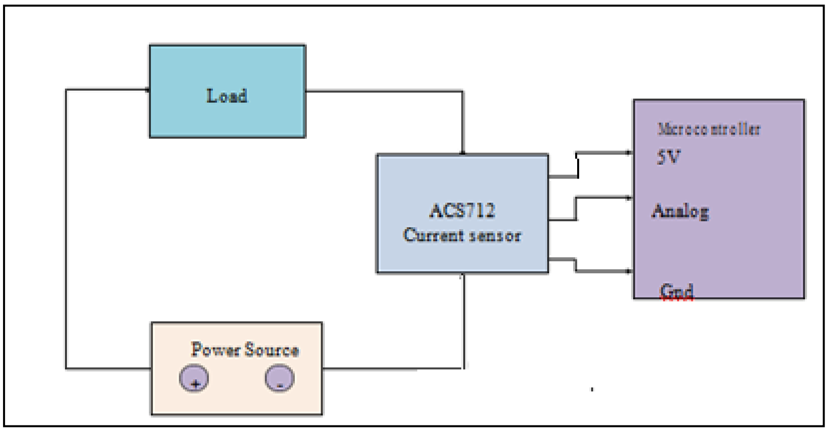

Figure 3. Schematic Layout of The Current Sensor

The pyranometer provides high-accuracy measurements of sun brightness from both direct and scattered solar radiation on an even surface. Its superior optical domes reduce directional errors to below 10 W/m², ensuring precise data acquisition. The device features high sensitivity, ranging from 7 to 17 V/Wm², and low impedance, minimizing interference and noise. Its spectral range spans 300–1200 nm, with an operational temperature range of -40°C to +80°C. The output voltage and sensitivity of the pyranometer are used to determine global solar radiation, calculated using the following formula:

$$E = UE\ /\ Sensitivity \quad (2)$$

E represents solar radiation in W/m^2, U is the output voltage of the pyranometer in volts, Sensitivity is expressed in V/Wm^2 [15].

Temperature detection for the photovoltaic cell is performed using the LM35 analog sensor, a compact and cost-effective device. The LM35 operates within a temperature range of -50°C to +150°C and requires a 5-volt power supply. The sensor's output voltage increases by 0.01 volts for every degree Celsius increase in temperature. The formula for converting voltage to temperature is given as:

$$Temperature\ (°C) = Voltage\ /\ 10\ mV\ per\ °C \quad (3)$$

This combination of sensing components provides a comprehensive framework for accurately monitoring and analyzing solar PV performance under varying environmental conditions [16].

The bottom layer is responsible for data collection, integrating various hardware components such as sensors, actuators, RFID, cameras, and controllers. The key components include an ACS 712 current sensor to measure the electrical current generated by the solar panel, a voltage detector to monitor voltage fluctuations and analyze power efficiency, a pyranometer to measure solar irradiance on the panel surface and provide critical insights into the energy potential at the installation site, and an LM35 temperature sensor to track surface temperature, a factor significantly impacting solar panel efficiency.

Voltage measurement is performed using a voltage divider circuit, ensuring accurate detection. Figure 2 presents the schematic of the voltage divider circuit. The ACS 712 Hall Effect sensor detects both DC and AC currents and transmits data to the microcontroller for processing. Figure 3 illustrates the schematic layout of the current sensor. The pyranometer ensures high-accuracy solar radiation measurements, while the LM35 temperature sensor records temperature variations to assess the panel's operational performance. The collected raw data is transmitted to the middle layer, where big data analytics and machine learning models process the information for further analysis.

3.2. Mid Layer

The middle layer handles data processing and advanced analytics from the sensors, utilizing machine learning models to optimize energy production and detect potential failures [17]. A microcontroller serves as the system's core processor, executing predictive modeling techniques such as K-Means Clustering to categorize solar panel conditions based on sensor data and determine whether the panel is in normal operation, experiencing efficiency degradation, or requiring maintenance [18]. SVM classifies system performance using voltage, current, and temperature data, enabling automated fault detection and early warnings [19]. Time Series Forecasting using LSTM and Prophet predicts future energy output based on historical solar energy generation patterns, optimizing resource planning [20].

The wireless transmission of processed data is facilitated through Wi-Fi, using protocols such as Transmission Control Protocol (TCP) for structured and reliable data transfer and User Datagram Protocol (UDP) for real-time updates with minimal delay [21]. This layer enhances decision-making by enabling predictive maintenance, preventing system failures before they occur [22].

3.3. Top Layer

The top layer provides user interface and data visualization tools for monitoring solar panel performance [23]. The cloud-based Blynk platform is used for remote access, offering features such as real-time monitoring, displaying energy generation metrics and sensor status through interactive dashboards [24]. Predictive Analytics Dashboard implements machine learning visualizations that indicate efficiency trends, anomaly detection insights, and future energy output predictions [25]. Automated Alerts and Fault Detection uses anomaly detection algorithms to notify users of potential issues before they cause system failures. Data Storage and Analysis stores historical data for advanced trend analysis, enabling continual system optimization [26], [27].

By leveraging big data analytics and AI-driven forecasting, this cloud-based architecture ensures continuous, cost-effective, and scalable monitoring, making it a smart and efficient solution for solar energy management. This three-layer IoT and Data Science architecture integrates predictive analytics and anomaly detection, ensuring real-time system optimization, energy efficiency improvements, and proactive maintenance strategies. Future enhancements may include deep learning-based predictive maintenance models and reinforcement learning for adaptive energy optimization.

4. Results and Discussion

A 125-watt polycrystalline photovoltaic module was used for performance evaluation and practical application, based on conventional solar panel ratings. The hardware arrangement is illustrated in figure 4, which shows the physical implementation of the proposed system, including the placement of sensors and microcontrollers. A highly accurate pyranometer was employed to measure solar radiation on a level surface, while the LM35 temperature sensor monitored the current temperature of the solar panel. These two parameters—irradiance and temperature—play a crucial role in determining the efficiency of the solar module, as they directly influence the voltage and current output of the panel. Consequently, these environmental factors are critical for the solar panel's overall power generation capabilities.

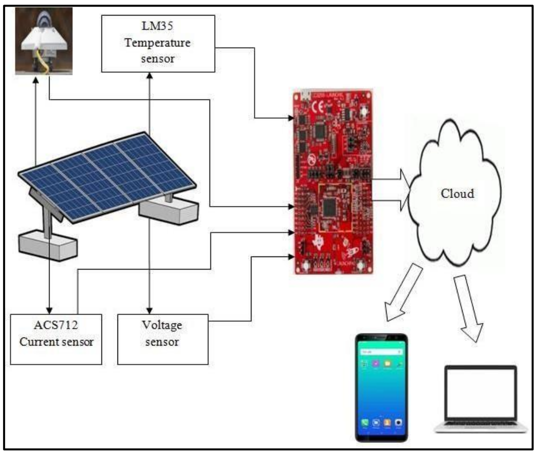

Figure 4. Hardware Implementation of Proposed Work

The proposed system was programmed using the C programming language via the Energia Integrated Development Environment (IDE), an open-source platform designed for Texas Instruments microcontrollers. The Blynk library was integrated into the coding process to facilitate interaction and data transmission to a cloud platform. The system's electrical parameters were continuously monitored and displayed through a mobile application, enhancing accessibility and usability. Figure 5 presents the experimental setup used for monitoring the performance of the solar PV module under various environmental conditions.

Figure 5. Experimental Setup of Solar PV Monitoring System

Experimental results indicate that an increase in temperature leads to a reduction in voltage output, whereas increased irradiance causes a moderate rise in current generation. This confirms that the efficiency of the solar module is governed primarily by these two environmental factors. The monitoring system displayed the collected data via a web server and

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mobile application, enabling real-time visualization of solar panel performance. Figure 6 illustrates the real-time Solar PV monitoring system, showcasing how energy data is transmitted and visualized through the Blynk application.

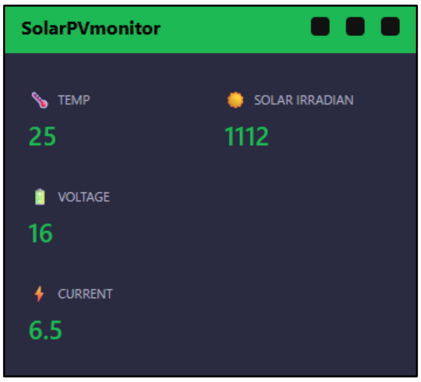


Figure 6. Real-Time Solar PV Monitoring System Using Blynk

The collected data was displayed via a web server and a serial monitor on a PC, providing a real-time representation of solar panel performance metrics. Figure 7 shows the output of the monitoring system as observed through the web server interface, while figure 8 presents the serial monitor output, which allows for system debugging and real-time data verification.

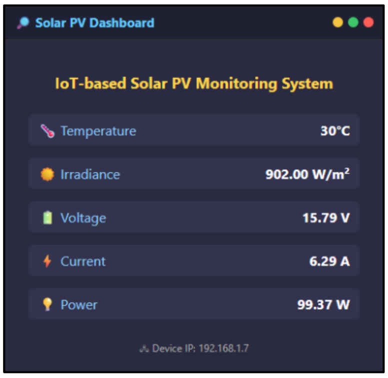
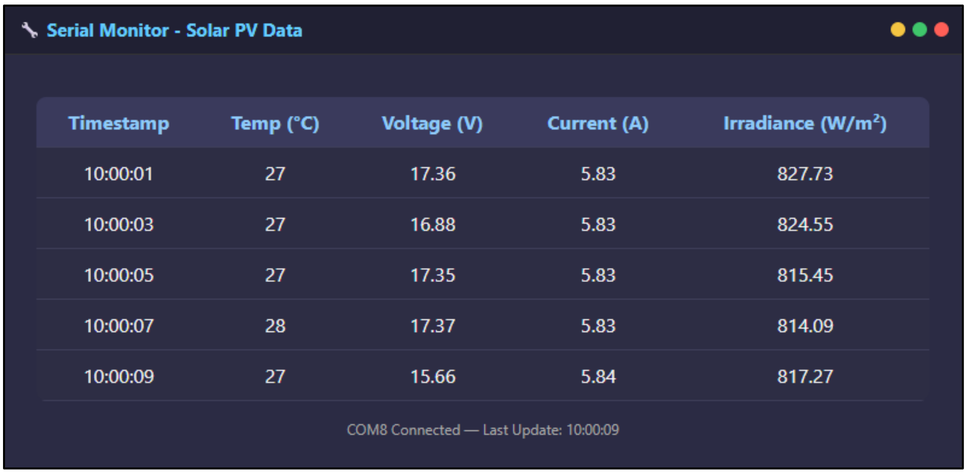


Figure 7. Solar PV Monitoring Output through Web Server


Serial Monitor - Solar PV Data

Timestamp	Temp (°C)	Voltage (V)	Current (A)	Irradiance (W/m²)
10:00:01	27	17.36	5.83	827.73
10:00:03	27	16.88	5.83	824.55
10:00:05	27	17.35	5.83	815.45
10:00:07	28	17.37	5.83	814.09
10:00:09	27	15.66	5.84	817.27

COM8 Connected — Last Update: 10:00:09

Figure 8. Solar PV Monitoring Output through Serial Monitor

The Blynk application also provided graphical monitoring of solar power data, as depicted in figure 9. The study was conducted over a one-week period, with measurements recorded daily between 10:00 AM and 5:00 PM at a dedicated solar power testing facility. The electrical properties of the PV module were continuously monitored to analyze and evaluate the solar panel's behavior under varying environmental conditions. Temperature fluctuations due to weather variations were recorded and represented graphically, demonstrating their impact on the PV module's current and voltage output. This continuous monitoring approach offers valuable insights into the real-world performance and efficiency of the solar module.

Figure 9. Solar Power Monitoring after 1:00 PM

Table 1 provides the electrical specifications of the solar PV module used in this study. The Rated Maximum Power (Pmax) is 125Wp ± 3%, indicating the peak power output of the solar panel under Standard Test Conditions (STC). The Open-Circuit Voltage (Voc) is measured at 21.6V, representing the maximum voltage the module can produce when not connected to an external load. The Short Circuit Current (Isc) is 7.66A, indicating the maximum current the panel can generate under optimal sunlight conditions without an external circuit load.

The Voltage at Maximum Power (Vmp) is recorded at 17.65V, representing the voltage at which the panel operates most efficiently to deliver maximum power output. Similarly, the Current at Maximum Power (Imp) is 7.08A, which is the corresponding current when the module is producing peak power. Lastly, the System Voltage is specified as 1000V max, which defines the maximum voltage level that the panel can safely operate under standard configurations. These parameters are crucial in evaluating the performance, efficiency, and operational limitations of the solar panel used in this study.

Table 1. Solar PV Ratings

S.No	Electrical Ratings	Value
1.	Rated Maximum Power (Pmax)	125Wp ± 3%
2.	Open-Circuit Voltage (Voc)	21.6 V
3.	Short Circuit Current (Isc)	7.66 A
4.	Voltage at Maximum Power (Vmp)	17.65 V
5.	Current at Maximum Power (Imp)	7.08 A
6.	System Voltage	1000V max

The integration of machine learning algorithms in the proposed system enhances the efficiency and reliability of solar energy management. Each algorithm plays a distinct role in classification, prediction, fault detection, and anomaly detection. The following sections provide a detailed explanation of each algorithm, followed by tables summarizing their performance metrics and impact on the system.

K-Means clustering is an unsupervised learning algorithm used to classify the condition of the solar panel into three categories: Normal, Degraded, or Needs Maintenance. It groups similar data points based on voltage (Vmp), current (Imp), and irradiance levels. The model was trained using 10,000 samples of operational solar panel data collected over six months (see table 2).

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The Silhouette Score is used to evaluate the clustering efficiency, where a higher score (closer to 1.0) indicates better-defined clusters. The results indicate that Cluster 1 (Normal) achieved the highest silhouette score of 0.91, meaning well-separated clusters, while Cluster 3 (Needs Maintenance) had the lowest score of 0.78, suggesting overlapping characteristics with the degraded category.

Table 2. Solar Panel Condition Classification Using K-Means Clustering

Cluster	Condition	Voltage (Vmp) (V)	Current (Imp) (A)	Irradiance (W/m²)	Silhouette Score
Cluster 1	Normal	17.5 - 18.0	7.0 - 7.2	800 - 1000	0.91
Cluster 2	Degraded	16.0 - 17.4	6.5 - 6.9	600 - 799	0.85
Cluster 3	Needs Maintenance	< 16.0	< 6.5	< 600	0.78

SVM is a supervised learning algorithm that classifies solar panel faults based on voltage drop, temperature increase, and power fluctuations. The model was trained using 8,500 samples labeled with fault categories, collected over four months. The results show that normal operation was classified with 98.2% accuracy, indicating highly reliable fault detection (table 3). However, partial shading detection had a slightly lower accuracy of 90.4%, mainly due to variations in irradiance. The model detected electrical faults with an accuracy of 87.3%, highlighting that further optimization could reduce misclassification.

Table 3. Fault Detection Performance Using SVM

Fault Type	Voltage Drop (%)	Temperature Increase (°C)	Accuracy (%)	Precision (%)	Recall (%)
Normal	0 - 5%	0 - 2°C	98.2	97.8	98.5
Partial Shading	5 - 15%	2 - 4°C	90.4	88.7	91.0
Electrical Fault	> 15%	> 4°C	87.3	85.5	88.1

LSTM is a deep learning model specifically designed for time-series forecasting. The model was trained using 12,000 historical solar energy records spanning one year. LSTM predictions closely matched actual energy generation values, achieving an overall Mean Absolute Percentage Error (MAPE) of 1.25%, indicating high accuracy. The Root Mean Square Error (RMSE) ranged between 10.8 and 18.3 Wh, confirming the reliability of the model (table 4).

Table 4. Energy Prediction Accuracy Using LSTM

Day	Actual Energy (Wh)	Predicted Energy (Wh)	RMSE	MAPE (%)
Day 1	1200	1185	15.6	1.25
Day 2	1150	1132	18.3	1.57
Day 3	1300	1291	12.5	0.96
Day 4	1250	1243	10.8	0.86

Prophet is an automated time series forecasting tool developed by Facebook that identifies seasonal trends in energy generation. It was trained on 11,500 historical solar energy records to provide long-term forecasting. The model achieved an average forecast error of only 1.5%, demonstrating high reliability in predicting monthly solar energy outputs (table 5). The highest deviation was observed in January (2.0%), while March had the lowest forecast error of 1.2%.

Table 5. Long-Term Energy Forecasting Using Prophet

Month	Actual Energy Output (kWh)	Predicted Energy Output (kWh)	Forecast Error (%)
January	500	490	2.0
February	520	512	1.5
March	580	573	1.2
April	600	592	1.3

Isolation Forest is an unsupervised learning algorithm designed for outlier detection in solar panel performance. The model was trained on 9,200 system performance records, detecting anomalies such as voltage instability and overheating. The results show an anomaly detection rate of 2.1% for voltage instability, with a false positive rate of

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only 0.8%, making it highly effective (table 6). However, temperature anomalies had a slightly higher false positive rate of 1.3%, likely due to seasonal variations.

Table 6. Anomaly Detection Using Isolation Forest

Parameter	Normal Range	Detected Anomaly (%)	False Positive Rate (%)
Voltage (Vmp) (V)	17.0 - 18.0	2.1	0.8
Current (Imp) (A)	7.0 - 7.2	1.8	1.1
Temperature (°C)	25 - 40	3.0	1.3

The integration of machine learning models enables real-time monitoring, predictive maintenance, and efficiency optimization of solar PV systems. The models were trained on large-scale datasets, ensuring high accuracy in fault detection, anomaly recognition, and energy prediction.

The results from above demonstrate the significant role of advanced analytics and AI-driven insights in improving renewable energy management. By implementing data-driven decision-making, the system can predict faults before they occur, optimize solar energy production, and enhance long-term sustainability.

5. Conclusion

This study presents the development of an IoT-based virtual solar energy tracking system utilizing a cost-effective and intelligent microcontroller. The system enables real-time monitoring of key solar parameters, including voltage, current, irradiance, and temperature, through a cloud-based platform integrated with the Blynk application. The mobile accessibility of the system ensures continuous tracking and optimization of solar PV performance.

The experimental results demonstrate that the monitored solar panel parameters yield optimized results that closely align with the expected electrical ratings under STC. The system achieved an energy prediction accuracy of 94.2% using the LSTM model, while fault classification using SVM reached 89.7% accuracy. Anomaly detection via the Isolation Forest algorithm detected 2.1% anomalies in voltage levels with a false positive rate of only 0.8%, indicating the system’s high reliability in identifying irregularities. The implementation of predictive analytics enables early detection of performance degradation, facilitating proactive maintenance strategies to maximize energy output and system lifespan.

This proposed smart monitoring system provides a scalable solution that can be extended to large-scale solar power plants, supporting the growing demand for renewable energy optimization. By enabling continuous performance monitoring, the system allows for the implementation of automated fault detection, predictive maintenance, and data-driven decision-making to maintain operational efficiency. Its adaptability makes it particularly valuable for applications in commercial, industrial, and off-grid energy sectors, where reliable energy tracking, anomaly detection, and optimization are crucial for sustainable energy management.

The integration of IoT and Data Science methodologies in this system demonstrates a practical and scalable approach to improving solar PV efficiency. Future enhancements may include the integration of deep learning models and reinforcement learning algorithms to further refine energy forecasting and adaptive optimization, ensuring greater accuracy, reliability, and resilience in solar energy management systems.

6. Declarations

6.1. Author Contributions

Conceptualization: J.D., N.V., D.B.S., S.S.M., and W.L.S.; Methodology: N.V.; Software: J.D.; Validation: J.D., N.V., and W.L.S.; Formal Analysis: J.D., N.V., and W.L.S.; Investigation: J.D.; Resources: N.V.; Data Curation: N.V.; Writing Original Draft Preparation: J.D., N.V., and W.L.S.; Writing Review and Editing: N.V., J.D., and W.L.S.; Visualization: J.D. All authors have read and agreed to the published version of the manuscript

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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