Development of an AI-Driven Autonomous Solar Panel Dirt Detection and Cleaning System using IoT Technology

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Abstract The accumulation of dust and dirt on solar panels significantly degrades energy production efficiency, often causing performance reductions ranging from 20% to 30%. Traditional cleaning methods rely heavily on manual labor, which incurs high maintenance costs and limits operational efficiency. To address this critical issue, this research aims to design and develop an automated solar panel dirt detection and cleaning system powered by Artificial Intelligence (AI) and Internet of Things (IoT) technologies. The primary objectives of this study are to create an autonomous mechanical cleaning apparatus, develop an AI model capable of accurately classifying dirt accumulation levels based on real-time environmental data, and implement a dedicated web application for remote system control and real-time performance monitoring.

The system architecture integrates a NodeMCU ESP-32S microcontroller with a comprehensive sensor array, including VEML7700 ambient light sensors, an SHT30 temperature and humidity sensor, and custom-designed voltage and current measurement circuits. These sensors continuously monitor the physical and electrical conditions of the solar panels, transmitting the data to a cloud-based MySQL database via JSON format. To evaluate the dirtiness level, a dataset of 15,689 environmental and electrical records was collected over 34 days to train and compare multiple machine learning algorithms (Decision Tree, k-NN, Naïve Bayes, and Random Forest) using the WEKA platform. The Random Forest algorithm was ultimately selected due to its robust ensemble learning capabilities, minimizing overfitting and providing stable predictions under varying environmental noise. The mechanical cleaning unit utilizes a Nema 17 stepper motor and a DC gear motor to drive a nylon brush across the panel surface automatically when triggered by the AI.

Experimental evaluations conducted in a real-world rooftop environment demonstrated the system's high reliability. When tested on a new dataset of 150 records, the Random Forest model achieved a classification accuracy of 92.00% and an impressive overall average F1-Score of 88.27% across three defined states: Clean, 15% efficiency drop, and 30% efficiency drop. Notably, the model exhibited 100% precision in detecting dirty states, ensuring no false mechanical triggers occurred during operation. The integrated Flutter-based web application successfully allowed users to monitor real-time metrics, review AI predictions, and override cleaning schedules remotely. In conclusion, this AI-driven autonomous system presents a highly viable, cost-effective solution for optimizing solar energy harvesting and reducing long-term operational maintenance.

Keywords: Artificial Intelligence, Solar Panel Cleaning, Internet of Things, Random Forest, Predictive Maintenance.

1. INTRODUCTION

The accumulation of dust and dirt on solar panels is a critical factor that severely impacts energy production efficiency. Dust deposited on the panel surfaces can reduce energy generation by 20% to 30%, though this impact varies depending on environmental conditions and the type of dust [15]. This accumulation significantly diminishes the amount of incident light, leading to a substantial decrease in the solar panels' energy conversion process.

Currently, most solar panel cleaning procedures rely heavily on manual labor or non-automated systems, which incur high operational costs and exhibit limited efficiency. The application of Artificial Intelligence (AI) and Internet of Things (IoT) technologies for real-time dust detection and automated cleaning represents a viable solution to maximize efficiency and reduce long-term energy losses. An AI-driven system can monitor the status of solar panels in real-time and autonomously trigger cleaning operations only when necessary, effectively minimizing energy waste and extending the lifespan of the panels.

Based on this framework, an automated solar panel dirt detection and cleaning system has been developed to align with clean energy initiatives and respond to growing future energy demands. This project utilizes an ESP-WROOM-32 microcontroller integrated with various IoT sensors—including current, voltage, light intensity, temperature, and humidity sensors—to collect environmental and electrical data. This data is utilized to train a Machine Learning model using the Random Forest algorithm to analyze the dirtiness level on the solar panels. When the system detects that the accumulated dirt exceeds a predefined threshold, the AI autonomously commands the mechanical cleaning apparatus to operate.

Beyond its automated cleaning capabilities, the system reports real-time measured data through a dedicated web application. Users can access relevant performance metrics and manually override or command the cleaning process remotely via this web interface.

The primary objective of this research is to design and develop an automated solar panel cleaning device powered by artificial intelligence. To achieve this, the project encompasses the development of an AI-driven dirt analysis system designed to accurately evaluate contamination levels by monitoring incident light intensity and the generated electrical power. Additionally, the scope involves designing the physical hardware for the automated mechanical cleaning mechanism alongside the development of a dedicated web application. This web interface is intended to facilitate remote equipment control, real-time status tracking, and the continuous display of the collected sensor data.

By implementing this comprehensive system, the project anticipates several significant benefits. Primarily, it aims to increase the overall energy production efficiency of solar panels through continuous and optimal cleaning operations. Furthermore, the integration of the web-based monitoring platform will greatly enhance operational convenience by allowing users to track dirt levels remotely, effectively eliminating the need for routine on-site physical inspections. Ultimately, the autonomous nature of this AI-driven solution is expected to substantially reduce the labor and maintenance costs traditionally associated with manual solar panel cleaning procedures.

2. Literature Review and Related Research

This chapter presents the fundamental concepts, theories, principles, and related research that support the development of the AI-based solar panel dirt detection and cleaning system. The literature review covers solar panel technology, hardware and software components, artificial intelligence principles, and a comparative analysis of related studies.

2.1 Solar Panel Technology and Solar Radiation

Photovoltaic (PV) cells convert solar radiation directly into direct current (DC) electricity. Currently, the three primary types of solar panels used are Monocrystalline, Polycrystalline, and Thin-Film solar cells. Monocrystalline panels offer the highest energy conversion efficiency, generally ranging between 18% and 25%. Polycrystalline panels, while having a slightly lower efficiency of 15% to 20%, demonstrate strong heat tolerance. However, the accumulation of dust, moss, and dirt significantly deteriorates the energy conversion efficiency of all panel types, making proper and timely cleaning crucial for long-term energy generation. Thailand's geographical location provides high solar radiation, averaging 18 to 20 MJ/m²/day throughout the year, which presents a high potential for solar energy harvesting if panels are maintained optimally.

2.2 Hardware Equipment

The autonomous cleaning system integrates various hardware components to ensure precise real-time monitoring and mechanical operation.

1) Microcontroller The NodeMCU ESP-32S acts as the core processing unit for the system. Featuring a dual-core processor, built-in Wi-Fi, and Bluetooth capabilities, the ESP-32S is highly suitable for IoT projects that require multi-tasking, sensor integration, and wireless data transmission.

2) Sensors to accurately monitor the environmental conditions affecting the solar panels, the system utilizes the SHT30 sensor for highly precise temperature and humidity measurements. Additionally, the VEML7700

ambient light sensor is utilized to accurately detect incident light intensity in lux.

3) Motors and Motor Drivers The cleaning mechanism utilizes Nema 17 stepper motors for precise positional control along the panel tracks. These are driven by TB6600 controllers capable of handling high-torque applications. DC gear motors (ZKE1032-2K-R50) are deployed for brush rotation, managed by BTS7960 high-current motor drivers to effectively eliminate accumulated dust.

4) Custom Circuits and Power Supply A dual output switching power supply (RD-35A) delivers stable 5V and 12V DC energy to the system. To safely measure the generated electrical power, the system incorporates custom voltage division and current measuring circuits using LF351N and LF353N operational amplifiers, combined with LA 25-NP non-contact current sensors.

2.3 Software and Artificial Intelligence

The software architecture leverages multiple programming languages and libraries to bridge the hardware and cloud infrastructure. Python is utilized for processing data and machine learning, C/C++ is used for programming the ESP32 via the Arduino IDE, and Flutter/Dart are utilized for web application development. Data transmission relies on the lightweight JSON format, connecting the IoT hardware to a MySQL relational database.

Artificial Intelligence (AI) plays a pivotal role in autonomously evaluating the level of dirtiness on the solar panels and triggering the cleaning apparatus. To evaluate the AI model's performance, the system employs statistical metrics including Accuracy, Precision, Recall, and F1-Score, which are specifically optimized to handle imbalanced classification data. Error metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are also utilized to evaluate the average magnitude of prediction errors [13].

2.4 Comparison of Related Research

A comparative analysis of existing literature highlights the specific technological gaps that this project aims to fulfill. Several studies have explored advanced computational methods for detecting dust accumulation on solar panels. For instance, Khadka et al. (2020) [6] investigated the use of machine learning for solar panel dirt detection, successfully achieving a 90% detection accuracy. However, a major limitation of their approach is its heavy reliance on large, pre-trained datasets rather than dynamically adapting to real-time environmental variables. Similarly, Cui et al. (2024) [3] introduced a highly accurate framework for offshore floating solar stations that utilizes image analysis to detect dust. While this method yields precise results, it demands complex image processing capabilities and the installation of high-quality cameras, which significantly increases computational requirements.

Conversely, other research has focused on mechanical and direct sensor-based cleaning systems. Maindad et al. (2020) [8] developed a motorized automatic cleaning system that operates on a fixed time schedule. Although this approach effectively reduces manual maintenance costs, it lacks the flexibility and efficiency of an AI-driven, real-time condition monitoring system. Addressing the need for remote management, Saisin et al. (2021) [16] developed a solar cleaner controlled via a mobile application; however, this system emphasizes manual remote control rather than true autonomous detection. Furthermore, Olorunfemi et al. (2023) [12] utilized TCS3200 color sensors integrated with an Arduino to detect dirt through changes in surface color. While this method provides valuable real-time data, it lacks the advanced predictive capabilities and precision found in ensemble machine learning algorithms.

Based on this comprehensive review, it is evident that existing systems either lack autonomous real-time adaptability or require overly complex hardware. Therefore, integrating physical sensor data—specifically voltage, current, and light intensity—with an ensemble learning model such as Random Forest provides a robust, cost-effective, and highly accurate solution for real-time autonomous cleaning that effectively bridges the current technological gap.

3. Research Methodology

This section outlines the comprehensive research methodology used to design, develop, and evaluate the AI-based solar panel dirt detection and cleaning system. The methodology encompasses the research framework, functional and non-functional requirements, hardware and software design, user interface development, and the mathematical formulations used for AI model evaluation.

3.1 Research Framework

The research framework is structured around the integration of Internet of Things (IoT) sensors and Artificial Intelligence (AI) to autonomously monitor and clean solar panels. Data collection was conducted using a prototype installed on the rooftop of South East Asia University, allowing for continuous solar irradiance exposure. The system captures environmental and electrical data every 5 minutes, specifically filtering for the operational hours of 07:00 to 17:00.

The collected dataset consists of continuous quantitative features: Temperature, Humidity, Light Intensity (from three sensors), Voltage, and Current. To train the AI model, the dataset was rigorously pre-processed to remove missing or anomalous values and was subsequently labeled into three categorical states: Clean, Dirty_15 (15% efficiency drop), and Dirty_30 (30% efficiency drop). The dataset of 15,689 records was split into 70% for training (10,982 records) and 30% for testing (4,707 records) to ensure robust model evaluation. Multiple machine learning algorithms were evaluated using the WEKA platform, including Decision Tree (J48), k-Nearest Neighbors (k-NN), Naïve Bayes, and Random Forest (Holmes et al., 1994) [5]. Random Forest was ultimately selected as the core AI model due to its high accuracy (97.46%), its ensemble learning architecture that minimizes overfitting, and its stability in predicting power degradation under varying environmental noise.

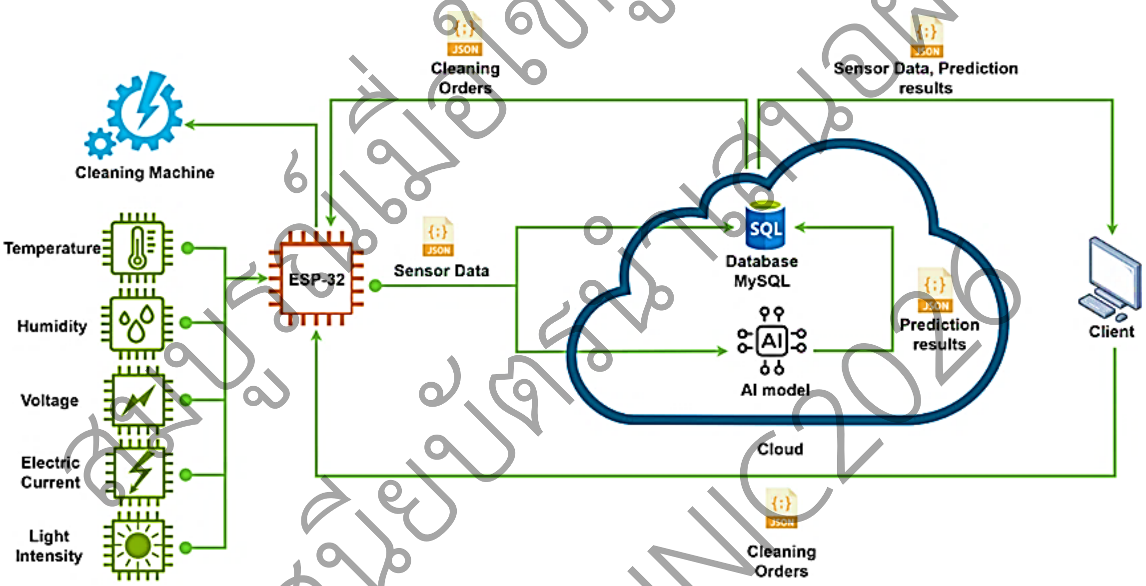

Fig. 1 System Framework

3.2 Mathematical Formulation for AI Evaluation

To rigorously evaluate the performance of the AI models, several statistical and error measurement equations were utilized.

Accuracy *(1)*: Measures the overall percentage of correct predictions made by the model across all classes [9].

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

Precision *(2)*: Measures the proportion of actual positive cases among all instances predicted as positive, indicating the model's exactness [9].

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

Recall (Sensitivity) *(3)*: Measures the proportion of actual positive cases that the model correctly identified, demonstrating its completeness [9].

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

F1-Score *(4)*: Represents the harmonic mean of Precision and Recall, which is particularly useful for evaluating models trained on imbalanced datasets [9].

$$F1 - Score = 2\,\frac{(Precision * Recall)}{(Precision + Recall)} \quad (4)$$

Mean Absolute Error (MAE) *(5)* and Root Mean Square Error (RMSE) *(6)*: These equations measure the average magnitude of prediction errors. RMSE gives higher weight to larger errors [2] and [19].

$$MAE = \frac{1}{n}\sum|y_i - \hat{y}_i| \qquad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \qquad (6)$$

Where y_i represents the actual value, $\hat{y}_i$ represents the predicted value, and n represents the total number of observations.

3.3 Functional and Non-Functional Requirements

To ensure the system addresses the operational challenges of solar maintenance, the following requirements were established:

• Functional Requirements: The system must allow users to register and securely log in. It must continuously monitor and display the real-time status of the solar panels (voltage, current, light intensity, temperature, and humidity). The system must utilize AI to analyze dirt accumulation and generate predictive reports. Furthermore, it must autonomously trigger the mechanical cleaning apparatus when dirt thresholds are exceeded, while also allowing users to manually initiate or halt the cleaning process remotely.

• Non-Functional Requirements: The software architecture must feature a responsive web interface accessible across diverse devices (mobile, tablet, desktop) [11]. The system must deliver data with minimal latency utilizing a lightweight JSON format for rapid IoT transmission [1]. Additionally, the hardware must be resilient to external environmental factors, incorporating custom noise-filtering circuits and robust enclosures.

3.4 Hardware Design

The hardware architecture acts as the physical foundation for the IoT and AI operations.

• Processing Unit: The core controller is the NodeMCU ESP-32S, chosen for its dual-core processing capabilities and integrated Wi-Fi, which bridges the physical sensors and the cloud infrastructure [4]. It is installed externally to the main control box to prevent signal interference and ensure stable wireless communication.

• Sensor Array: The system employs three VEML7700 ambient light sensors to capture precise irradiance data. Because these sensors share identical I2C addresses, a PCA9548A multiplexer is utilized to facilitate concurrent data acquisition [17]. An SHT30 sensor measures localized temperature and humidity [7]. For electrical monitoring, custom circuits were designed: an LA 25-NP Hall-effect sensor coupled with an LF351N operational amplifier measures current, while an ISO122P isolating amplifier combined with an LF353N operational amplifier precisely measures voltage while preventing ground-loop noise.

• Cleaning Actuators: The cleaning mechanism operates on an aluminum slide rail. It is driven laterally by a Nema 17 Stepper Motor (controlled by a TB6600 driver), while a 12V ZKE1032 DC Gear Motor (controlled by a BTS7960 driver) rotates the nylon brush to safely eradicate surface debris without scratching the panels.

3.5 Software Design with UML

The software architecture is engineered using modern object-oriented programming frameworks, incorporating Python for AI development (Scikit-learn, Pandas) and Dart/Flutter for the user interface [10] and [14]. Unified Modeling Language (UML) diagrams were designed to define system behaviors and relationships:

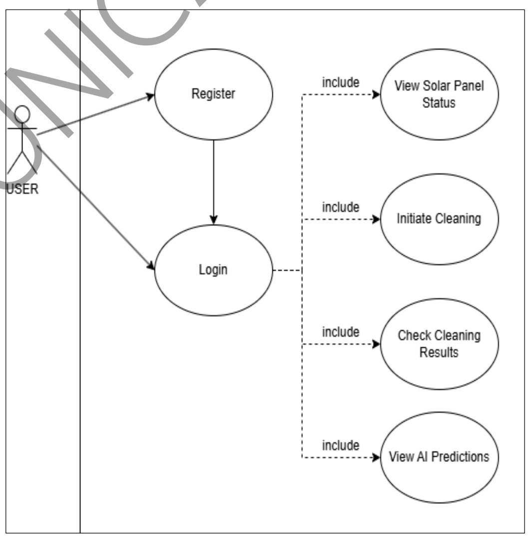

Fig. 2 Use case Diagram

• Use Case Diagram: Defines interactions between the primary actor (User) and core system functionalities, specifically Register, Login, View Solar Panel Status, Initiate Cleaning, Check Cleaning Results, and View AI Predictions, as shown in the figure 2.

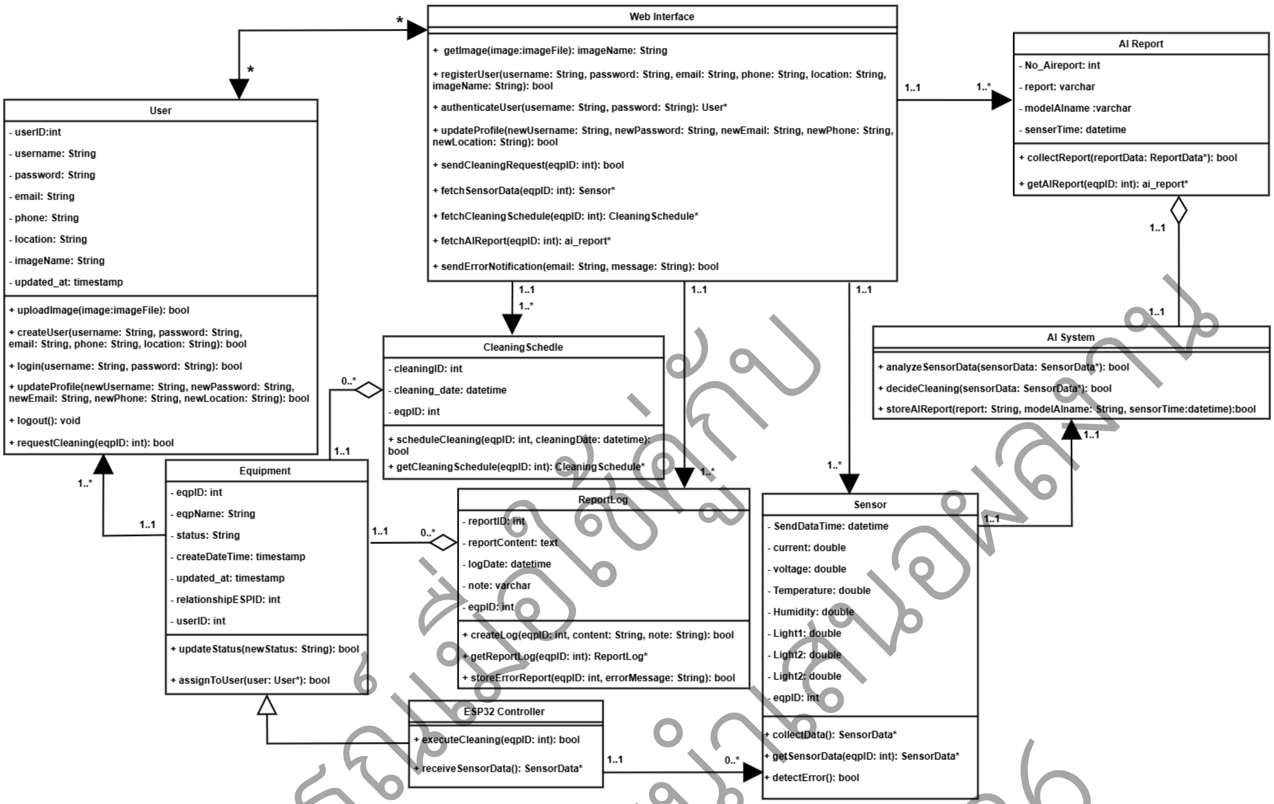

Fig. 3 Class Diagram

• Class Diagram: Maps the structural relationships between objects. The User interacts with the Web Interface, which acts as a central hub. The Equipment class houses multiple Sensor entities that feed data to the AI System. Based on AI analysis, the ESP32 Controller interacts with the *CleaningSchedule* to execute mechanical tasks, logging all activities into the *ReportLog*, as shown in the figure 3.

• Activity Diagrams: Illustrate the sequential flow of specific tasks. For example, the cleaning activity flow verifies equipment readiness, initiates the stepper and DC motors, updates the UI in real-time, and concludes by logging the performance comparison (before and after cleaning).

• Sequence Diagrams: Detail the chronological message exchange. The Dirt Analysis process highlights the ESP32 fetching sensor data every 5 minutes, transmitting it to the AI for evaluation, and subsequently triggering the Activator (brush/motor) if the dirt accumulation exceeds pre-defined operational thresholds.

• Entity-Relationship (ER) Diagram: The relational MySQL database relies on six primary tables: users, equipment, sensor, ai_report, report_log, and cleaning_schedule. Foreign keys (e.g., eqpID) interconnect these tables to ensure seamless data traceability from user ownership down to specific localized sensor logs [18].

3.6 User Interface (UX/UI) Design

The user interface adheres to Universal Design principles, ensuring accessibility and ease of use across different device capabilities. The frontend was developed using the Flutter framework to guarantee cross-platform responsiveness (mobile, tablet, desktop) using layout builders and media queries. The color palette was intentionally selected to reflect clean energy and modern technology: Blue and Light Green symbolize cleanliness and eco-friendly solar energy, while White and Light Gray provide a clean, modern backdrop that enhances data legibility. The interface features intuitive navigation, presenting a comprehensive "Dashboard/Show Status" page for real-time monitoring of electrical and environmental metrics, a "History" page for reviewing past cleaning performance, and an "AI Report" page displaying predictive maintenance insights calculated by the Random Forest algorithm. Performance testing was successfully conducted on low-end smartphones, legacy tablets, and entry-level laptops to ensure fluid UI responsiveness globally, as shown in the figure 4 and 5.

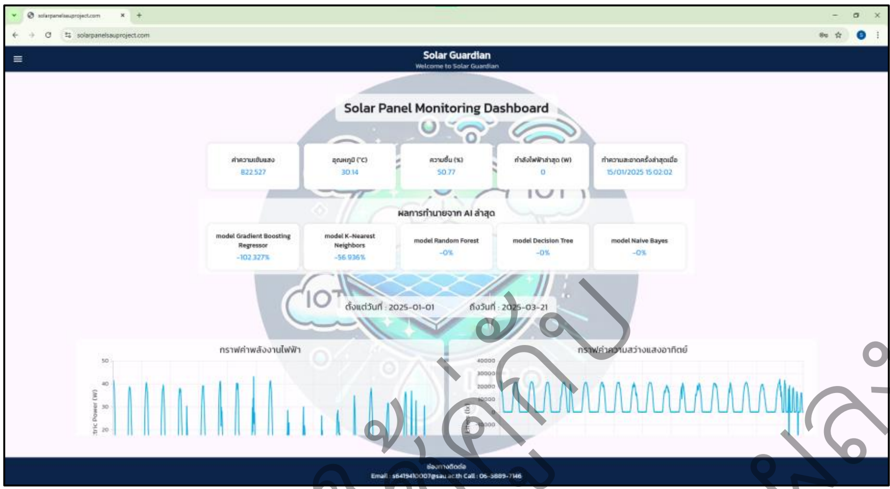

Fig. 4 User Interface of Solar Panel Monitoring Dashboard

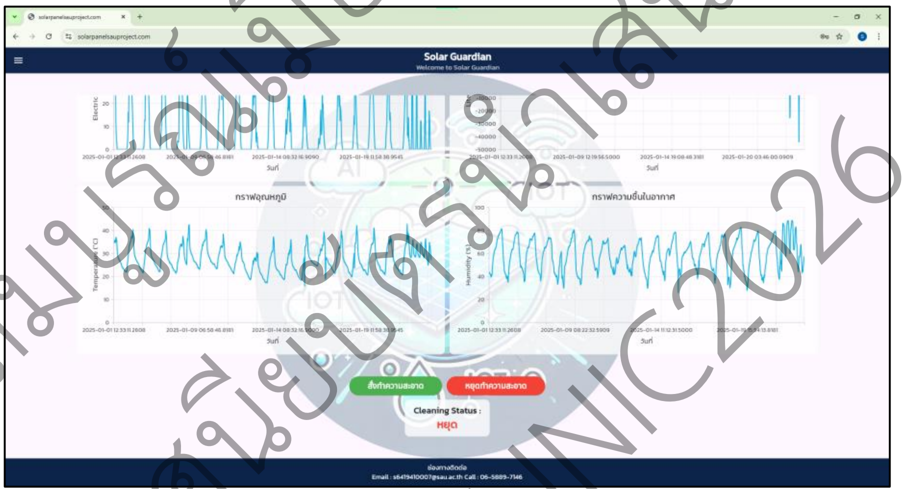

Fig. 5 User Interface of Solar Guardian

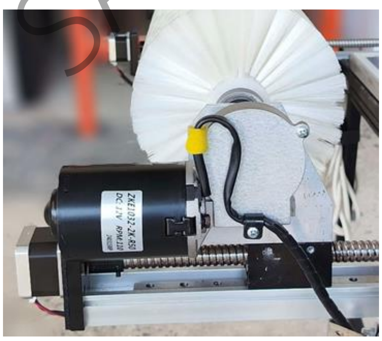

Fig. 6 Solar panel cleaning system

Fig. 7 DC Motor model ZKE1032 - 2K - R50 DC

Fig. 8 Main Control Box

4. Results and Discussion

This section presents the experimental results of the automated solar panel dirt detection and cleaning system. The Random Forest model was evaluated using a newly collected dataset to classify the dirtiness levels of the panels in a real-world environment. The performance was assessed using statistical metrics including Accuracy, Precision, Recall, F1-Score, False Positive Rate (FPR), and True Negative Rate (TNR).

4.1 Experimental Setup and Data Collection

The experiment was conducted under real-world environmental conditions by installing the prototype on the rooftop of South East Asia University, an area with continuous sunlight exposure. Data was collected over a period of four days, from March 17 to March 20, 2025, yielding a total of 150 new data records to evaluate the model's performance on unseen data. The ESP32 microcontroller functioned as the central processing unit to acquire data from the sensor array—measuring light intensity, voltage, current, temperature, and humidity—and transmitted it for AI analysis.

Python and the Scikit-learn machine learning library [14] were utilized to analyze the prediction errors and rigorously evaluate the model. Table 1. illustrates a sample of the environmental and electrical data captured during the experimental period.

Table 1. Sample of the experimental data collected from sensors.

current (A)	voltage (V)	Tmp (°C)	Humi (%)	Light1 (Lux)	Light2 (Lux)	Light3 (Lux)	Date Time
2.65	4.87	30.62	51.40	20390.86	19371.11	20256.31	17/3/2025 13:52:00
3.69	6.79	34.97	41.44	22436.81	21328.12	22570.45	17/3/2025 14:16:00
4.20	7.75	31.61	48.88	21762.66	21068.70	23777.28	17/3/2025 11:33:00
3.94	7.23	34.41	35.22	22502.25	19145.78	21432.27	18/3/2025 12:30:00
3.82	7.02	34.46	39.33	21407.85	19842.97	22211.48	18/3/2025 13:13:00
3.34	6.12	33.60	46.27	23873.13	19406.13	21400.93	19/3/2025 13:13:00
2.21	4.03	27.99	54.23	14906.42	15148.80	20185.34	19/3/2025 14:51:00

4.2 Performance of the Random Forest Model

The trained Random Forest model was deployed to predict the dirtiness levels—categorized as Clean, Dirty_15 (15% efficiency drop), and Dirty_30 (30% efficiency drop)—based on the new sensor data. The classification performance was comprehensively analyzed using a Confusion Matrix, as presented in Table 2.

Table 2. Confusion Matrix of the Random Forest model on the test dataset.

	Predicted		
	Clean	Dirty$_{15}$	Dirty$_{30}$
Actual Clean	50	0	0
Actual Dirty_15	6	44	0
Actual Dirty_30	12	0	38

Based on the Confusion Matrix, the system's performance metrics were calculated as follows:

- Accuracy: The model successfully predicted the correct dirtiness level for 92.00% (± 0.56) of the overall dataset.
- Precision: The model demonstrated a precision of 73.53% for the "Clean" class, indicating that when it predicted a panel as clean, it was correct 73.53% of the time. Remarkably, the model achieved a perfect 100% precision for both the "Dirty_15" and "Dirty_30" classes, indicating zero false positives when classifying a panel as dirty.
- Recall (Sensitivity): The model achieved a 100% recall for the "Clean" class, successfully identifying all genuinely clean panels. For the "Dirty_15" and "Dirty_30" classes, the recall was 88% and 76%, respectively. This indicates a slight tendency for the model to misclassify some dirty panels as clean.
- F1-Score: The F1-Score, which provides a harmonic mean of precision and recall for imbalanced datasets, was 84.8% for

"Clean," 93.6% for "Dirty_15," and 86.4% for "Dirty_30." This resulted in an impressive overall average F1-Score of 88.27% across all classes.

• False Positive Rate (FPR) and True Negative Rate (TNR): The model exhibited an FPR of 18%, indicating a moderate probability of false alarms. Consequently, the TNR was 82%, reflecting the model's strong reliability in correctly identifying clean panels and avoiding unnecessary cleaning operations.

4.3 Discussion and System Limitations

The experimental results validate that the Random Forest algorithm is highly effective for autonomous solar panel monitoring, achieving an overall prediction accuracy of 92.00% in real-world conditions. The 100% precision rate in detecting the "Dirty_15" and "Dirty_30" states is particularly advantageous for the automated cleaning framework, as it guarantees that mechanical cleaning actuators will never be triggered unnecessarily due to a false "dirty" prediction.

However, the evaluation also highlights certain system limitations. The lower recall observed in the "Dirty_30" class (76%) suggests that the model occasionally fails to identify heavily soiled panels, classifying them as clean instead. Furthermore, the AI's predictive capabilities are highly dependent on sensor integrity; physical degradation of the sensors over time will inevitably diminish the model's accuracy. The predictions are also sensitive to rapid meteorological variations, and the model has not yet been validated in extreme environments characterized by heavy dust accumulation, such as desert regions. Lastly, because the current software architecture does not utilize Reinforcement Learning, the AI cannot dynamically update its knowledge base or learn from real-time data anomalies as they occur.

5. Conclusion and Recommendations

This section summarizes the overall outcomes of the automated solar panel dirt detection and cleaning system, discusses the identified limitations, and provides strategic recommendations for future research and development.

5.1 Summary of Results

The development and implementation of the AI-based solar panel cleaning system demonstrated high precision in evaluating panel contamination levels. By utilizing the Random Forest model, the system achieved a prediction accuracy of 92.00% (± 0.56) and an average F1-Score of 88.27% under real-world environmental testing conditions. The integration of physical sensors—measuring light intensity, voltage, current, temperature, and humidity—enabled the Artificial Intelligence to accurately assess the condition of the panels. Once the evaluated dirtiness exceeded predefined thresholds, the system successfully and autonomously triggered the mechanical cleaning apparatus.

Furthermore, the development of a dedicated web application allowed users to seamlessly control the system and monitor the real-time status of the solar panels from a remote location. Overall, the developed system comprehensively fulfilled the project's core objectives, successfully combining automated hardware design, AI-driven dirt analysis, and remote web-based control.

5.2 Limitations Recommendations

Despite the prototype's high performance, practical deployment has revealed several notable limitations within the current system architecture. Foremost among these is the lack of continuous learning capabilities; because the system does not currently incorporate Reinforcement Learning, the artificial intelligence model cannot dynamically adapt to or update itself from new, real-time data anomalies as they occur. Additionally, the system exhibits a profound dependency on continuous internet connectivity to transmit sensor data to the cloud server. This reliance means that any network instability, or a complete lack of internet access, can result in significant data loss. Consequently, deploying the system in geographically remote locations with inadequate technological infrastructure renders it highly susceptible to severe network latency and connectivity failures.

To address these constraints and enhance the system's overall efficiency, scalability, and adaptability, several strategic recommendations are proposed for future iterations. A critical advancement would be the implementation of Edge Computing coupled with advanced AI. Shifting data processing from a centralized cloud server directly to IoT edge devices, such as the ESP32 microcontroller, would substantially reduce server load and latency. Furthermore, the integration of Reinforcement Learning would empower the system to continuously adapt to evolving environmental conditions without the need for manual retraining. To overcome the aforementioned connectivity challenges in remote or off-grid locations, future designs should also upgrade the communication protocol from standard Wi-Fi to Long Range (LoRa) or Narrowband IoT (NB-IoT) networks, thereby drastically improving system reliability.

Further hardware and operational enhancements are also recommended to optimize performance. For the mechanical apparatus, exploring low-pressure water spraying systems as an alternative or supplement to the existing nylon brushes may yield superior cleaning efficiency in specific environments. Operationally, the implementation of predictive maintenance techniques would allow the AI to analyze long-term dust accumulation trends, enabling it to forecast the precise, optimal timing for cleaning operations. This schedule could be further refined by integrating machine learning with weather forecasting APIs, which would prevent the system from executing redundant cleaning cycles immediately prior to a rainstorm. Finally, future research should explore a transition toward a sensorless architecture. By utilizing Computer Vision through AI-powered cameras to visually inspect panel dirtiness, the system could provide a robust alternative to direct physical measurements, thereby significantly reducing the long-term hardware degradation and maintenance costs associated with traditional physical sensors.

5.3 CONCLUSION

The developed prototype successfully achieved the research objectives by autonomously detecting dirt accumulation and executing cleaning operations effectively using real-world data. Although limitations exist regarding dynamic learning and cloud connectivity, this prototype establishes a robust, highly functional foundation. With further integration of edge computing, advanced communication protocols, and computer vision, this system can be significantly expanded to provide a highly scalable and cost-effective maintenance solution for large-scale solar power generation in the future.

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