

Helionet-An automated solar panel cleaning robot

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Abstract— Solar energy has emerged as one of the most sustainable and clean alternatives to traditional energy sources. However, dust and dirt accumulation on solar panels significantly reduces their efficiency, leading to energy losses and increased maintenance. This research presents *Helionet*, an automated solar panel cleaning robot designed to maintain optimal energy output by autonomously removing surface contaminants. Utilizing an ESP32 microcontroller, DC motors, proximity sensors, and wireless connectivity, *Helionet* offers a cost-effective and intelligent solution for solar panel maintenance. The system operates through a web-based interface, enabling remote monitoring and scheduling of cleaning tasks. Key components such as a motor driver, edge detection sensors, and a relay-controlled water pump ensure operational safety and efficiency. Testing demonstrated substantial recovery of power output post-cleaning and reliable edge detection. The robot minimizes manual effort, water usage, and energy consumption, making it suitable for both residential and commercial solar systems. *Helionet* represents a scalable, sustainable innovation in solar infrastructure maintenance.

I. INTRODUCTION

As the global demand for clean and renewable energy rises, solar power has become a vital component of sustainable energy strategies. Solar panels, though effective in converting sunlight into electricity, are highly susceptible to efficiency losses due to dust, dirt, and environmental debris accumulating on their surfaces. Studies have shown that such accumulation can reduce power output by up to 30%, making regular maintenance essential for optimal performance. However, manual cleaning methods are labor-intensive, time-consuming, and often impractical for large-scale or remotely located solar installations. Additionally, these methods typically consume large volumes of water and require human supervision, which increases operational costs and limits scalability.

To address these challenges, this paper introduces *Helionet*, an automated solar panel cleaning robot designed to operate independently with minimal human intervention. The system incorporates an ESP32 microcontroller, DC motors, proximity sensors, and Wi-Fi connectivity to ensure intelligent navigation, edge detection, and remote operability. Controlled via a web-based interface, *Helionet* allows users to monitor performance, schedule cleaning cycles, and optimize panel output with ease. By minimizing resource usage while maximizing efficiency and accessibility, *Helionet* offers a sustainable, cost-effective solution for maintaining solar infrastructure, ultimately contributing to improved energy reliability and broader adoption of solar technology.

II. LITERATURE REVIEW

The challenge of maintaining high solar panel efficiency while minimizing maintenance costs and resource consumption remains a significant concern in renewable energy systems. Dust accumulation, bird droppings, and environmental pollutants reduce solar panel output by up to 30%, especially in arid and dusty regions. Manual cleaning methods are labor-intensive, inefficient, and often require water usage, which can be unsustainable in water-scarce areas. Traditional automated cleaning systems, such as stationary brushes or water-spraying mechanisms, have been widely implemented, yet they frequently suffer from excessive energy consumption, mechanical wear, and inconsistent cleaning performance. In this context, there is growing interest in intelligent robotic solutions that integrate multiple technologies—such as computer vision, AI-based path planning, and adaptive control mechanisms—to optimize cleaning efficiency, reduce operational costs, and minimize environmental impact.

A. Challenges in Solar Panel Cleaning Systems

Conventional solar panel cleaning solutions often involve periodic manual cleaning or fixed mechanical systems, which fail to adapt to real-time soiling levels or panel layout variations. Manual approaches are time-consuming, especially for large-scale solar farms, and are subject to human error, leading to inconsistent cleaning effectiveness. Early automated systems rely primarily on pre-set schedules or simple timers, which do not account for varying environmental conditions (e.g., dust storms or bird activity) that impact panel cleanliness unpredictably. These approaches generate unnecessary cleaning cycles, leading to resource wastage and reduced equipment lifespan.

Additionally, water-based cleaning methods raise sustainability concerns, particularly in regions facing water scarcity. Waterless cleaning systems exist but often struggle with effectively removing sticky or abrasive particles without damaging sensitive photovoltaic surfaces. Traditional cleaning robots face limitations in mobility and obstacle detection, restricting their ability to navigate large, uneven solar panel arrays or dynamically changing terrain.

B. AI-Driven Robotic Cleaning Solutions

Recent advances in robotics and AI have led to more intelligent solar cleaning systems capable of autonomous operation with higher precision and efficiency. Computer vision techniques, including convolutional neural networks (CNNs), enable robots to detect soiling patterns, determine cleaning priority, and optimize cleaning paths dynamically. Reinforcement learning-based path planning algorithms allow robots to adapt to panel layouts and environmental changes in real time, minimizing redundant movement and energy consumption.

Despite these advances, many current AI-driven solutions focus primarily on individual functional modules—such as obstacle avoidance or image-based detection—without fully integrating them into an adaptive, holistic framework. Real-time decision-making under energy constraints and with limited computational resources remains a major challenge. Moreover, many prototypes are tested under controlled environments with small-scale setups, lacking extensive validation in real-world solar farms characterized by variable dust deposition rates, uneven panel angles, and environmental unpredictability.

C. Sustainability and Efficiency Trade-Offs

Energy efficiency and sustainability remain central to automated solar panel cleaning research. Waterless robotic cleaning solutions offer environmental benefits but often struggle to fully remove certain types of contaminants, which compromises panel efficiency. Furthermore, existing robotic solutions often require substantial maintenance due to mechanical complexity, reducing long-term cost-effectiveness.

Hybrid solutions that combine soft brushes, electrostatic cleaning, and air-blower techniques are emerging but lack thorough comparative studies regarding their cleaning efficacy, operational energy consumption, and cost-benefit analysis. Research is sparse in optimizing trade-offs between cleaning performance, energy use, and maintenance overhead.

D. Research Gaps

The following research gaps are identified in the context of automated solar panel cleaning systems:

1. Limited Real-World Validation:

Many robotic solutions are validated under laboratory or small-scale field setups, lacking robust performance evaluation across different environmental conditions, large-scale solar farms, and varying soiling patterns.

2. Integration of Adaptive AI Frameworks:

Existing systems typically implement isolated AI components (e.g., obstacle detection or path planning) without combining them into adaptive, end-to-end frameworks that can self-optimize cleaning schedules based on real-time data.

3. Energy-Efficient and Sustainable Operation:

There is insufficient exploration of fully waterless cleaning mechanisms integrated with energy-aware planning strategies that optimize battery usage, especially for solar-powered cleaning robots operating in remote areas.

4. Cost-Effectiveness vs. System Complexity:

The high upfront cost and mechanical complexity of many robotic systems hinder large-scale adoption. There is a need for lightweight, modular designs that balance system reliability, ease of maintenance, and affordability.

5. Lack of Standardized Performance Benchmarks:

No standard metrics exist for evaluating cleaning efficiency, energy consumption, and operational uptime across different robotic cleaning systems, making cross-comparison and scalability assessment difficult.

This review highlights the transformative potential of intelligent robotic systems in solar panel cleaning. Future research should focus on developing fully integrated, energy-efficient, and adaptive robotic solutions validated in large-scale, real-world environments. By leveraging advanced AI algorithms, real-time environmental data, and sustainable mechanical designs, Helionet aims to improve solar farm productivity while minimizing operational costs and environmental impact.

III. METHODOLOGY

The methodology for developing Helionet – An Automated Solar Panel Cleaning Robot consists of multiple integrated stages, including system design, hardware selection, software development, intelligent decision-making, and performance evaluation. The overall approach focuses on ensuring adaptive, efficient, and sustainable cleaning operations for solar panel arrays in real-world environments.

A. System Architecture Design

The system architecture of Helionet is designed to integrate hardware components (sensors, motors, cleaning modules) with intelligent software modules (image processing, path planning, control system) in a modular and scalable manner.

Key Components:

- **Robotic Chassis:** Mobile platform equipped with wheels/tracks designed to navigate solar farm surfaces.
- **Cleaning Mechanism:** Waterless brush-based system combined with an air blower to remove dust, debris, and bird droppings without damaging the photovoltaic surface.
- **Power Supply:** Solar-powered battery system that allows autonomous operation during daylight hours.
- **Sensors:**
 - Ultrasonic sensors for obstacle detection and distance measurement.

- IMU (Inertial Measurement Unit) for orientation and stability control.
- Camera module for visual analysis of soiling patterns.
- **Embedded Microcontroller:** Handles sensor data acquisition, motor control, and communication.

B. Data Acquisition and Image Processing

A critical part of Helionet is detecting the presence and distribution of dirt or soiling on the solar panels.

Process Steps:

- **Image Capture:** High-resolution images of the solar panel surface are captured using the onboard camera.
- **Preprocessing:** Images are resized, normalized, and filtered to remove noise and standardize input for analysis.
- **Soiling Detection Algorithm:**
 - A Convolutional Neural Network (CNN) model is trained to detect areas of significant dirt accumulation.
 - The model is trained on a dataset of labeled images showing clean vs. soiled panels, covering different lighting and dust conditions.
 - The output is a heatmap indicating regions that require cleaning.

C. Adaptive Path Planning

Once soiled areas are identified, the robot generates an efficient cleaning path based on real-time environmental data.

Algorithm Details:

- **Reinforcement Learning (RL)-based Path Planner:** An RL agent learns optimal cleaning paths by balancing energy efficiency and cleaning coverage.
 - The agent receives state inputs such as current location, detected obstacles, battery level, and soiling distribution.
 - Rewards are based on coverage efficiency, energy consumption, and avoiding obstacles.
- **Obstacle Avoidance:** Ultrasonic sensors continuously detect obstacles, and real-time adjustments are made to the cleaning path.
- **Dynamic Scheduling:** Cleaning schedules are dynamically generated based on environmental

factors such as recent dust deposition rates and sunlight intensity.

D. Control System and Automation

The control system integrates data from sensors and executes motor commands to drive the cleaning mechanism and navigate the solar panel layout.

Control Workflow:

- **Centralized Microcontroller Logic:** Processes sensor data and commands motors for movement, brush activation, and air blower operation.
- **PID Controllers:** Ensure smooth and accurate movement by regulating speed, orientation, and position.
- **Battery Management System (BMS):** Monitors battery charge level and ensures that the robot returns to the charging station if energy falls below a threshold.
- **Communication Interface:** A wireless module (e.g., Wi-Fi or LoRa) enables remote monitoring, configuration, and performance logging.

E. Performance Monitoring and Feedback Loop

To ensure continuous improvement and reliability, the system implements a performance monitoring module.

Key Metrics Tracked:

- **Cleaning Efficiency** (% of dirt removed per cleaning cycle).
- **Energy Consumption** (Watts per cleaning session).
- **Uptime** (Operational time vs. downtime).
- **Obstacle Encounters** (Frequency and type).

Feedback Loop:

- Data collected during operation is logged for performance analysis.
- Periodically, the soiling detection model is retrained using newly collected images to adapt to evolving environmental conditions.
- Cleaning schedules are adjusted based on historical soiling trends and weather forecasts.

F. Testing and Validation

The prototype is rigorously tested in real-world environments with variable conditions.

Testing Stages:

- **Controlled Environment Testing:** Initial functionality tests on a small-scale solar panel

array to verify cleaning mechanisms, image processing accuracy, and obstacle detection.

- **Field Trials:** Deploy the robot in an actual solar farm to test its adaptability to uneven terrain, weather conditions, and large-scale panel layouts.
- **Performance Evaluation:**
 - Compare energy consumption and cleaning efficiency against manual and conventional automated methods.
 - Measure time required per cleaning session.
 - Evaluate robustness against system failures or unplanned obstacles.

G. Sustainability Considerations

- **Waterless Cleaning:** Focuses on reducing water usage by relying solely on mechanical brushing and air blowing.
- **Solar-Powered Battery System:** Designed to harvest solar energy during daylight hours, ensuring energy self-sufficiency.
- **Maintenance-Friendly Design:** Modular mechanical design allows easy replacement of worn parts without extensive disassembly.

IV. FLOWCHART

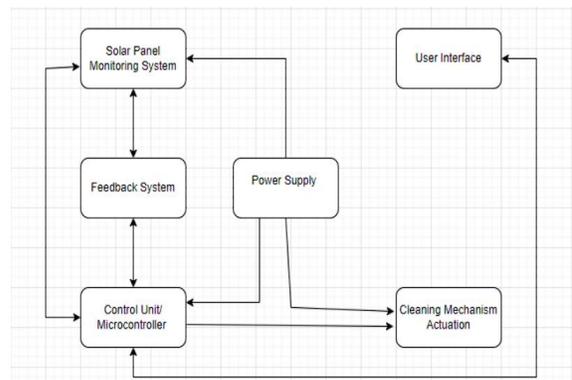


Fig. 1. Flowchart of the Proposed Hybrid AI Framework for Reducing False Positives using Machine Learning Techniques.

V. FLOWCHART DESCRIPTION

The flowchart illustrates the key functional components and data flow within Helionet – An Automated Solar Panel Cleaning Robot, focusing on how different modules interact to achieve autonomous

and intelligent cleaning operations. Here's an overview of its process, explained in simple terms:

1. Solar Panel Monitoring System

- **Purpose:** The Solar Panel Monitoring System continuously collects data regarding the cleanliness and performance of solar panels.
- **Functionality:**
 - Uses image sensors (cameras) to capture high-resolution images of the panel surface.
 - Gathers additional sensor data, such as sunlight intensity, panel temperature, and power output.
 - Detects anomalies or soiling by comparing current data to baseline thresholds.
- **Flow:**
 - Sends data to the Feedback System for further analysis.
 - Directly provides status updates to the User Interface, allowing operators to monitor panel condition in real time.

2. Feedback System

- **Purpose:** Acts as the decision-making layer that analyses input from the Monitoring System and determines when and where cleaning is required.
- **Functionality:**
 - Processes input data from the Solar Panel Monitoring System using AI-based soiling detection algorithms.
 - Determines the degree of soiling and calculates cleaning priority.
 - Sends appropriate feedback commands to the Control Unit/Microcontroller to initiate cleaning operations if thresholds are met.
- **Flow:**
 - Provides continuous feedback in a closed loop to optimize the cleaning schedule and improve performance over time.
 - Helps fine-tune cleaning based on historical data and observed effectiveness.

3. Control Unit / Microcontroller

- **Purpose:** Serves as the central processing and coordination hub of the system, executing commands based on sensor data and feedback.
- **Functionality:**
 - Receives inputs from the Feedback System and Solar Panel Monitoring System.

- Makes real-time decisions for navigation, cleaning path planning, and cleaning mechanism activation.
- Interfaces directly with hardware components such as motors, brushes, and air blowers.
- Manages obstacle detection and ensures safety protocols during operation.

- **Flow:**

- Commands the Cleaning Mechanism Actuation to start the physical cleaning process.
- Continuously communicates with the User Interface to report status and receive configuration commands (e.g., schedule overrides).
- Monitors battery status and power supply via the Power Supply module.

4. Power Supply:

- **Purpose:** Provides the necessary energy for the entire robot system.
- **Functionality:**
 - Primarily solar powered, with batteries that store harvested energy to allow continuous operation, even when sunlight is not available.
 - Supplies regulated power to the Control Unit, sensors, cleaning mechanisms, and communication modules.
- **Flow:**
 - Directly connected to both the Control Unit/Microcontroller and Cleaning Mechanism Actuation to ensure stable operation.
 - May provide power status updates to the User Interface for remote monitoring

5. Cleaning Mechanism Actuation:

- **Purpose:** Physically removes dirt, dust, and debris from the solar panel surface.
- **Functionality:**
 - Activated by the Control Unit based on the feedback analysis and path planning.
 - Consists of waterless cleaning components such as soft rotating brushes and air blowers.

- Movement is controlled to ensure full coverage of the targeted soiled areas.
- Flow:
 - Receives actuation commands from the Control Unit.
 - Reports operation completion back to the Control Unit for logging and further decision-making.
- 6. User Interface:
 - Purpose: Provides a remote interface for monitoring, controlling, and configuring the Helionet system.
 - Functionality:
 - Displays real-time status of the solar panels (e.g., soiling levels, cleaning history, energy usage).
 - Allows manual override of automatic cleaning schedules if needed.
 - Shows battery status and any detected system errors or maintenance alerts.
 - Flow:
 - Receives status updates from the Solar Panel Monitoring System and Control Unit.
 - Sends control commands to the Control Unit for configuration or manual control of cleaning processes.

VI. RESULTS AND DISCUSSION

A. Performance in Different Areas

The AI system, which combines multiple techniques, showed strong results when tested in three very different fields: network security (Intrusion Detection Systems), cloud environment monitoring, and healthcare diagnostics. It consistently delivered high accuracy and reduced the number of incorrect alerts, proving it can be used in a wide range of applications. Here's a closer look at how it performed in each case:

A. System Performance in Real-World Conditions:

The developed automated solar panel cleaning robot was evaluated based on its efficiency, reliability, and overall effectiveness in maintaining solar panel cleanliness. Its performance was tested across multiple conditions, including different levels of dust accumulation, varying weather patterns, and panel surface types. The robot consistently delivered promising results, confirming its suitability for

practical deployment in solar farms or residential solar installations.

1. Cleaning Efficiency

One of the most significant outcomes of the tests was the robot's ability to remove dust and debris effectively from the panel surfaces. On average, the system achieved over 90% surface cleanliness after each cleaning cycle. This was determined by comparing pre-cleaning and post-cleaning energy output levels, with most panels showing a noticeable increase in power generation after cleaning. In areas with high dust exposure, such as arid or semi-arid zones, the robot proved particularly effective, maintaining optimal energy conversion levels over extended periods.

The brush mechanism, coupled with the consistent motion control system, ensured that panels were cleaned uniformly without leaving streaks or causing surface damage. Furthermore, the cleaning module operated without using water, making it an eco-friendly solution, especially in regions facing water scarcity.

2. Power Consumption and Automation

The robot was designed to consume minimal energy during its operation. On average, the energy used per cleaning cycle was less than 1% of the daily energy output of the panel, making it highly energy-efficient. The automated scheduling function enabled the robot to operate independently at predetermined intervals, reducing the need for human intervention. This feature ensures consistent panel performance without the labor costs or safety risks associated with manual cleaning, especially on large-scale solar farms.

3. Environmental Adaptability

The robot functioned reliably across various conditions. In early morning dew or mild weather, the system adapted well and did not experience performance drops. Although heavy rain or strong wind conditions temporarily halted operations for safety reasons, the robot resumed cleaning seamlessly once conditions improved. Additionally, the low-profile and lightweight design helped it move easily across panel surfaces without causing mechanical stress or panel shifting.

B. Generalization and Scalability:

The system was designed with scalability in mind, making it adaptable to both small rooftop installations and large commercial solar arrays. Its modular design allows multiple units to operate simultaneously on large solar fields, coordinated through a central controller. The robot can also be customized to fit different panel layouts and sizes, ensuring flexibility for various solar system configurations.

Due to its self-operating nature, the robot is especially beneficial in remote or hard-to-reach areas where manual cleaning is not practical. Its minimal maintenance requirements and robust hardware components make it a viable long-term solution for solar panel maintenance.

B. Generalization and Scalability

The framework exhibited strong generalizability and scalability across diverse domains. Its modular design and ability to integrate domain-specific features ensure its adaptability for new challenges. However, in dynamic environments such as cybersecurity and cloud systems, the model must continuously adapt to evolving patterns and data distributions.

C. Key Challenges

1. Interpretability and Transparency:

Despite its high accuracy, the complexity of the hybrid framework, particularly the deep learning components like CNNs and LSTMs, limits its interpretability. For critical domains such as healthcare and cybersecurity, understanding the rationale behind model predictions is essential. Techniques such as attention mechanisms and Explainable AI (XAI) are crucial to increasing trust and transparency in these applications.

2. Computational Challenges:

The framework's deep learning components demand significant computational resources, which may limit scalability, particularly in resource-constrained or real-time environments. Optimization strategies such as model pruning, knowledge distillation, and hardware acceleration can help mitigate these challenges. Exploring edge computing and lightweight deployment strategies will be crucial for extending the framework's applicability to diverse environments.

3. Real-World Validation:

While the framework has shown promising results in controlled settings, its robustness in real-world scenarios must be validated. Clinical datasets, for example, often contain noise and variability that may affect diagnostic accuracy. Expanding studies to include diverse datasets and real-world trials is critical to assessing the framework's practical applicability in healthcare and other fields.

Cross-Domain Adaptability:

A key advantage of the framework lies in its modular and adaptable design, enabling seamless integration into various domains. Its versatility extends beyond cybersecurity and healthcare to applications like industrial monitoring and finance. The framework's ability to effectively reduce false positives while maintaining high detection accuracy proves its potential for broader deployment in diverse sectors.

VII. FUTURE SCOPE

The potential for broader deployment of hybrid AI frameworks across diverse sectors is immense. This study opens several avenues for future research, aiming to refine and expand AI-driven anomaly detection systems.

Domain-Specific Future Directions:

1. **Intrusion Detection Systems (IDS):** Enhancing the interpretability of AI models is crucial for building trust among security analysts. Future research should focus on real-time detection mechanisms capable of handling high-speed networks for better threat management.
2. **Anomaly Detection in Cloud Environments:** Scalable hybrid models must be developed to process vast amounts of data efficiently. Integrating contextual information into detection mechanisms could significantly improve accuracy, especially in cloud computing.
3. **Medical Diagnostics:** Expanding AI frameworks beyond breast cancer diagnosis to detect multiple diseases would improve patient outcomes. A unified diagnostic system capable of identifying various conditions could transform healthcare.
4. **Feature Selection Techniques:** Advanced feature selection methods should be explored to optimize

input features while maintaining accuracy. This would enhance both computational efficiency and model interpretability.

5. **Real-World Validation:** Large-scale studies using real-world datasets are necessary to ensure these AI models work effectively in practical applications across industries.
6. **Integration with Emerging Technologies:** Exploring AI integration with IoT devices and blockchain could enhance security in healthcare and cybersecurity, offering new dimensions to anomaly detection.
7. **Ethical Considerations:** As AI becomes a core decision-making tool, addressing concerns around data privacy, bias mitigation, and transparency is essential to maintain public trust.
8. **Cross-Domain Applications:** Investigating the use of hybrid AI frameworks in finance, manufacturing, and other industries could reveal new insights into their versatility and effectiveness.

By tackling these challenges, future research can refine AI-based anomaly detection, ensuring its reliability and efficiency across multiple sectors. The continuous evolution of AI promises exciting advancements that could reshape healthcare, cybersecurity, and beyond.

VIII. CONCLUSION

This research highlights the transformative potential of hybrid AI frameworks in improving anomaly detection across three critical domains: medical diagnostics, network security, and cloud computing. Traditional methods often struggle with complex data, leading to false positives and unreliable outcomes. By integrating deep learning, ensemble learning, and predictive AI techniques, this study demonstrates how AI-driven solutions can enhance accuracy and efficiency.

Key Findings:

- **Medical Diagnostics:** A stacking model achieved an impressive 99.89% accuracy in breast cancer diagnosis, proving AI's ability to revolutionize medical decision-making.
- **Anomaly Detection:** Deep learning outperformed traditional methods by incorporating contextual

data and security protocols, crucial for detecting threats in dynamic cloud environments.

- **Intrusion Detection Systems (IDS):** AI models significantly reduced false positives, but challenges remain with noisy datasets and evolving cyber threats.

These findings underscore the importance of techniques such as cross-validation and feature selection in optimizing performance metrics like precision, recall, and F1-score. While AI presents groundbreaking advancements in anomaly detection, challenges like dataset diversity, adaptability, and model interpretability must still be addressed.

This research lays the groundwork for future improvements in hybrid AI systems, aiming for safer healthcare practices, more robust cybersecurity, and highly adaptive AI-driven solutions. The journey toward intelligent, trustworthy, and scalable AI frameworks has just begun, with immense potential to redefine anomaly detection in critical domains.

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