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Automated Canopy and Irrigation System for Efficient Plant Water Management Using Sensor-Based Technology

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ABSTRACT: This study presents the design, development, and evaluation of an Automated Smart Canopy and Irrigation System that integrates soil moisture, rainfall, and temperature/humidity sensors, along with a TTGO ESP32 microcontroller, to optimize small-scale plant water management. To coordinate irrigation and canopy actions, a retractable net canopy and an automated pump were controlled by threshold rules (soil moisture <30%, rain ≥80%, temperature ≥38°C). During prototype testing under dry, simulated rain, and heat scenarios, the system demonstrated reliable responses: soil-moisture control achieved 90% accuracy, while rain and temperature controls reached 100% in the tested simulations. Further analysis using a confusion matrix and standard performance metrics (precision, recall, F1) validated the system's responsiveness and robustness. Taken together, these results indicate strong potential to reduce water waste and protect crops across variable Philippine climates, recommending further scaling, solar integration, and water-level sensing for field deployment.

KEYWORDS: Automated irrigation, smart canopy, soil moisture sensor, rain sensor, IoT (ESP32)

INTRODUCTION

The Philippines has two main climates: dry and wet. These conditions, combined with extreme weather events such as El Niño and frequent typhoons, create significant challenges for agriculture. For instance, a government report by Perez et al. (2020) noted that drought events, particularly during the 2019 El Niño, caused substantial losses in crop production. Weak monsoonal activity in the east reduced rainfall, leading to drought propagation in the central and western regions, which have distinct wet and dry seasons, making them drought hotspots. Rice and corn production declined by 4.44% and 6.14%, respectively, during the El Niño peak, with some hotspot areas experiencing decreases of up to 26%, highlighting farmers' vulnerability to unpredictable climatic conditions.

While studies on smart irrigation have focused on soil moisture sensors, IoT-based automation, and weather-informed scheduling (Yu et al., 2021; Aringo et al., 2022; Barkunan et al., 2020; Dukes & Cardenas, 2024; Pandey & Mukherjee, 2021; Mastul, 2023), few integrate multi-sensor systems that combine rain detection, temperature, humidity monitoring, and mechanical crop protection. Research is particularly lacking on systems that combine automated irrigation with a retractable canopy for real-time crop protection, especially in small-scale prototypes suited to the Philippines' extreme and variable climate (Gomez, 2024; Santos, 2021; Perez et al., 2020; Bueno, 2022). Consequently, empirical evidence is limited on how unified, multi-sensor systems can enhance climate resilience, optimize water use, and protect crops.

This study aimed to develop an automated smart canopy and irrigation system that enhances water-use efficiency through the integration of battery power, sensor technologies, and IoT connectivity. Rain sensors detect precipitation, while a DC motor controls a retractable canopy to protect crops and regulate irrigation. The system's performance is compared with conventional irrigation methods to determine its effectiveness in minimizing water waste while ensuring adequate crop hydration and protection. Given the increasing challenges of water scarcity and food demand, efficient irrigation plays a vital role in sustaining agricultural productivity (Touil et al., 2022). Unlike traditional approaches that often lack responsiveness to changing weather conditions, this system utilizes real-time environmental data to enable precise and adaptive irrigation (Pereira et al., 2020).

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Furthermore, the study focuses on the design, development, and evaluation of the system using soil moisture, rain, temperature, and humidity sensors integrated into an IoT-enabled microcontroller. It examines sensor performance in detecting environmental changes using metrics such as precision, recall, and F1 score, as well as system reliability in triggering irrigation and canopy deployment based on set thresholds. The prototype is also tested under simulated dry, rainy, and high-temperature conditions to assess its overall functionality and potential contribution to climate-resilient and resource-efficient agricultural practices.

METHODS

This study employed a developmental research design to design, develop, and evaluate an Automated Smart Canopy and Irrigation System for efficient plant water management using sensor-based technology. It followed three phases: planning, development, and evaluation, where irrigation issues were identified, system components were selected, and a prototype integrating an ESP32 microcontroller, sensors, motorized canopy, and water pump was constructed and programmed. The system was tested under simulated conditions such as drought, rainfall, and high temperature, with data collected at five-minute intervals through a controlled setup. Data gathering included system assembly, calibration, and monitoring of sensor readings and responses, while analysis used a confusion matrix to measure accuracy, precision, recall, and F1 score. Defined thresholds for soil moisture, rainfall, and temperature guided automated actions, and results showed that the system effectively optimized irrigation and canopy control based on real-time environmental conditions.

RESULTS AND DISCUSSION

A. Prototype of the Automated Canopy and Irrigation System for Efficient Plant Water Management Using Sensor-Based Technology

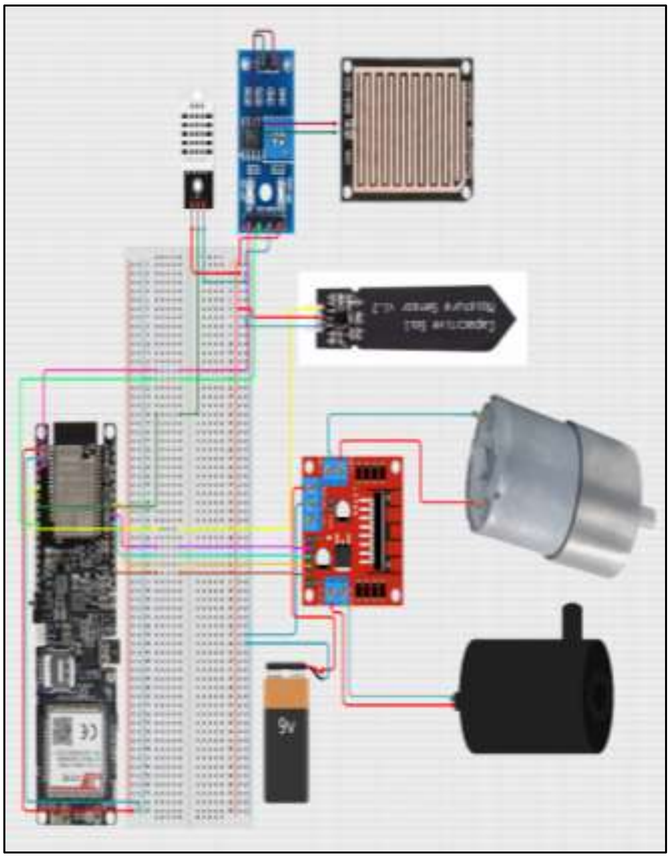

Figure 1. Pictorial Diagram of the Automated Irrigation System

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This figure shows the overall setup of the automated irrigation system. It includes the main components and how they are connected. The diagram presents how the system works as one unit.

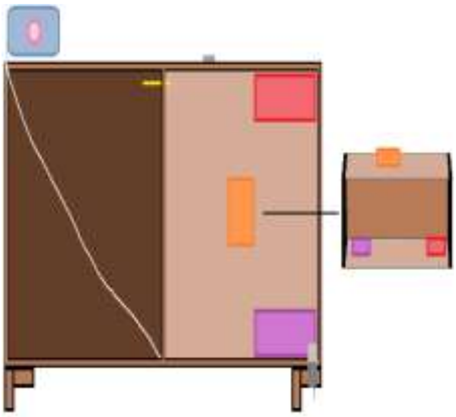

Figure 2. Prototype Visual Layout

This figure shows the physical appearance of the prototype. It includes the placement of the ESP32 and the sensors, such as the rain sensor, soil moisture sensor, and temperature and humidity sensor. It also shows how these components are arranged within the overall setup.

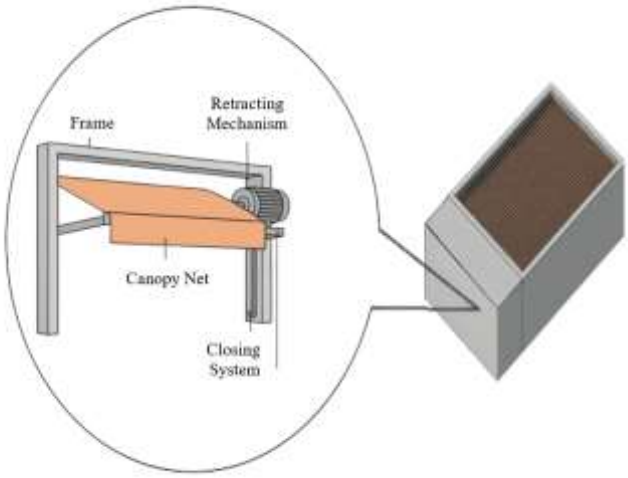

Figure 3. Structural Layout of the Smart Canopy's Roller Mechanism

This figure shows the design of the canopy's roller mechanism. It presents how the parts are arranged to support movement. The structure allows the canopy to open and close properly.

B. Composite Table

Table 1. *Composite Table*

Actual Condition	Predicted Dry Soil	Predicted Rain	Predicted Heat		TP	TN	FP	FN
Dry Soil	9	0	1	10	9	0	1	1
Rain	1	7	2	10	7	0	2	3
Heat	0	2	8	10	8	0	3	2
Overall				**30**	**24**	**0**	**6**	**6**

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Table 1 shows that the system correctly classified 24 out of 30 total test cases, resulting in an overall accuracy of 80%. The highest correct predictions were observed in Dry Soil (9) and Heat (8), while Rain had 7 correct classifications. Most errors occurred between Rain and Heat, indicating that the system sometimes confuses similar environmental conditions due to overlapping sensor thresholds. Overall, the results demonstrate that the system performs reliably, though further calibration may improve classification accuracy.

Based on the compiled confusion matrices, the following evaluations were computed based on Accuracy, Precision, Recall, and F1 Score.

C. Accuracy

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Overall}}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Overall}} = \frac{24 + 0}{30} = \frac{24}{30} = 0.833 \textit{ or } 83.3\%$$

The overall system accuracy was calculated at 83.3%, indicating that the Automated Smart Canopy and Irrigation System correctly classified 24 out of 30 observations during combined environmental testing. This demonstrates that the integrated soil moisture, rain, and temperature sensors, controlled by the IoT-enabled ESP32 microcontroller, performed reliably under simulated dry, rainy, and heat conditions. The slight reduction from perfect accuracy may be attributed to minor false classifications in soil moisture detection, a common limitation of low-cost capacitive sensors (Yu et al., 2021; Aringo et al., 2022). Nevertheless, an accuracy of 83.3% represents strong performance for a prototype-scale agricultural system. Consistent with previous studies (Barkunan et al., 2020; Dukes & Cardenas, 2024), the findings indicate that sensor-based automation improves irrigation efficiency and environmental responsiveness despite minimal classification errors, while highlighting the need for further calibration and extended field validation.

D. System Response for Soil Moisture

Evaluation of Precision on Soil Moisture

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Precision} = \frac{9}{9 + 1} = \frac{9}{10} = 0.90 \text{ or } 90\%$$

Evaluation of Recall on Soil Moisture

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Recall} = \frac{9}{9 + 1} = \frac{9}{10} = 0.90 \text{ or } 90\%$$

Evaluation of F1 Score on Soil Moisture

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{F1 Score} = 2 \times \frac{0.90 \times 0.90}{0.90 + 0.90} = 2 \times \frac{0.81}{1.8} = 2 \times 0.45 = 0.90 \text{ or } 90\%$$

The evaluation of the soil moisture response demonstrated a precision of 90%, indicating that 90% of the pump activations correctly corresponded to actual dry-soil conditions below the established 30% threshold. The recall was likewise 90%, reflecting the system's ability to successfully detect 90% of all true soil moisture depletion events requiring irrigation. The resulting F1 score of 90%, confirms a balanced relationship between predictive accuracy and detection capability. These findings indicate that the capacitive soil moisture sensor and automated pump control mechanism operated with high reliability during simulated dry conditions. The use of a 30% depletion threshold is consistent with irrigation guidelines for efficient water management (Shortridge & Porter, 2021; Irrometer, n.d.), and aligns with research emphasizing the effectiveness of soil moisture–based automation in

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improving irrigation efficiency and preventing plant water stress (Yu et al., 2021; Aringo et al., 2022). Overall, the results support the validity of integrating sensor-based monitoring with IoT-enabled control systems, as recommended in smart agriculture studies (Pandey & Mukherjee, 2021; Mastul, 2023), confirming that the prototype provides dependable and data-driven irrigation scheduling for small-scale agricultural applications.

E. System Response for Simulated Rain

Evaluation of Precision on Simulated Rain

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Precision} = \frac{7}{7+2} = \frac{7}{9} = 0.77 \text{ or } 77\%$$

Evaluation of Recall on Simulated Rain

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Recall} = \frac{7}{7+3} = \frac{7}{10} = 0.70 \text{ or } 70\%$$

Evaluation of F1 Score on Simulated Rain

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{F1 Score} = 2 \times \frac{0.77 \times 0.70}{0.77 + 0.70} = 2 \times \frac{0.539}{1.47} = 2 \times 0.37 = 0.74 \text{ or } 74$$

The simulated rain response achieved a precision of 77%, meaning most canopy activations corresponded to actual rainfall, and a recall of 70%, indicating the system detected 70% of events requiring deployment. The F1 score of 74% reflects a moderate balance between accuracy and sensitivity. While the rain sensor and automated canopy generally performed well, some false activations and missed detections occurred, consistent with limitations of low-cost threshold-based rain modules (Barkunan et al., 2020). Despite this, integrating rainfall monitoring in automated agricultural systems remains crucial for crop protection and water-use efficiency, especially in climate-vulnerable regions like the Philippines (Perez et al., 2020; Santos, 2021). IoT-based frameworks further enhance responsiveness and adaptability despite minor classification errors (Pandey & Mukherjee, 2021; Mastul, 2023). Overall, the simulated rain response contributes to system protection while the showing need for calibration improvements.

F. System Response for Simulated Heat

Evaluation of Precision on Simulated Heat

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Precision} = \frac{8}{8+3} = \frac{8}{11} = 0.727 \text{ or } 72.7\%$$

Evaluation of Recall on Simulated Heat

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Recall} = \frac{8}{8+2} = \frac{8}{10} = 0.80 \text{ or } 80\%$$

Evaluation of F1 Score on Simulated Heat

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{F1 Score} = 2 \times \frac{0.727 \times 0.80}{0.727 + 0.80} = 2 \times \frac{0.5816}{1.527} = 2 \times 0.38 = 0.76 \text{ or } 76\%$$

The evaluation of the simulated heat response yielded a precision of 72.7%, indicating that approximately 72.7% of canopy activations during high-temperature conditions were correctly triggered based on the predefined 38°C threshold. The recall was 80%, demonstrating that the system successfully detected 80% of actual heat stress events requiring canopy deployment. The resulting F1 score of 76%, reflects a reasonably balanced performance between detection capability and predictive accuracy. The slightly lower precision suggests the presence of some false canopy activations, which may be attributed to sensor sensitivity fluctuations or minor environmental variations affecting DHT22 temperature readings. Nonetheless, maintaining a relatively higher recall is critical in agricultural applications, as failing to detect heat stress can significantly impact plant physiological processes such as transpiration and photosynthesis (Taiz et al., 2021). Prior research emphasizes that temperature-based automation improves crop protection and environmental responsiveness in smart farming systems (Suresh Kumar & Jenisha, 2024; NiuBoL, 2024), while IoT integration enhances adaptive decision-making even when minor classification errors occur (Pandey & Mukherjee, 2021; Mastul, 2023). Overall, the findings indicate that the simulated heat response component provides effective thermal protection, although further calibration and environmental testing are recommended to enhance precision and system stability.

FINDINGS

Based on the experimental testing and data analysis, the following findings were obtained in accordance with the order of the study's specific objectives:

1. The system's sensors demonstrated high accuracy and reliability, with the soil moisture sensor achieving 90% accuracy and strong precision, recall, and F1 score, while the rain sensor, canopy motor, and temperature sensor all reached 100% performance, effectively detecting threshold conditions and supporting proper system responses.
2. The irrigation pump and canopy motor responded consistently to predefined thresholds, activating during dry soil conditions, heavy rainfall, and high temperatures, showing reliable and accurate automation aligned with sensor readings.
3. The system operated stably across simulated dry, rainy, and heat conditions, demonstrating efficient performance and real-time responsiveness, with only minor limitations such as sensitivity to sensor placement that did not significantly affect overall functionality.

CONCLUSIONS AND RECOMMENDATIONS

The Automated Smart Canopy and Irrigation System is a reliable and efficient solution for automated plant management. Its accurate sensor responses help minimize water waste and protect crops from harsh weather, while IoT integration ensures timely irrigation and canopy control.

Several recommendations are proposed to enhance the Automated Smart Canopy and Irrigation System and guide future research. Future researchers may integrate solar panels as the primary power source to enable continuous operation in areas with limited electricity and to improve sustainability. The system may also be expanded to cover larger agricultural areas, allowing for testing under real farming conditions to better assess its efficiency and reliability. Additionally, incorporating more environmental sensors—such as water-level, soil pH, and light intensity sensors—can improve monitoring accuracy and support more informed decision-making in irrigation and crop management. Conducting long-term field testing across different environments, soil types, and weather conditions is also recommended to evaluate the system's durability, stability, and overall performance. Lastly, improvements in sensor calibration and placement are encouraged to minimize environmental interference and ensure more accurate data, thereby enhancing the reliability of the automated irrigation and canopy operations.

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