

IoT-Based Drip System Using NodeMCU Module and Arduino UNO for Hydroponics

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Abstract: Hydroponic farming is a widely used method that utilizes nutrient-rich water instead of soil to grow plants. Several studies showed that new technologies have been implemented in hydroponic farming, particularly to improve its irrigation system. Thus, this study incorporated the Node MCU and Arduino Uno module. The system will use the system hardware and the Blynk IoT application, in which real-time readings of the sensors will automatically be displayed on the LED display on the panel and the phone. This research used an experimental design. It utilized the descriptive-comparative design in interpreting the data to determine the differences in the average activation time between the system hardware and the Blynk IoT application. The system has been programmed using the Node MCU and Arduino Uno module, and sensors have been installed to determine the temperature and soil moisture in hydroponics. Four hundred trials have been conducted to test the different functions of hydroponics. The results indicate that in terms of the function in water and AI mode, utilizing Blynk IoT and system hardware vary significantly. The system activates at an average of 7.41 with a standard deviation of 1.40 seconds. The water mode and AI mode operations are at an average of .32 and 1.80 and have a standard deviation of 0.14 and 0.22 seconds, respectively. Furthermore, the p-value is 0.000, less than 0.05, rejecting the null hypothesis.

Keywords: hydroponic farming, Arduino UNO, NodeMCU module, Philippines, quantitative research

I. Introduction

Environmental degradation remains one of the most pressing challenges of the 21st century, particularly in the field of agriculture. Traditional farming methods, while effective for centuries, have led to significant ecological issues such as soil depletion, excessive freshwater consumption, greenhouse gas emissions, and contamination due to pesticide and fertilizer overuse (AlShrouf, 2017). With the global population expected to reach nearly 9.7 billion by 2050, there is mounting pressure to innovate agricultural practices to ensure food security while minimizing environmental harm (Islam, 2025). This demand is further intensified by climate change, urbanization, and land scarcity, especially in developing and densely populated countries. In light of these challenges, there is an urgent call to adopt more sustainable, resource-efficient, and technologically enhanced approaches to food production that are adaptable to both rural and urban contexts.

One promising innovation is hydroponic agriculture, a soil-less method of cultivating plants using nutrient-enriched water solutions. This method addresses many of the drawbacks of conventional farming by offering more control over nutrient delivery, water conservation, space efficiency, and year-round crop production (Khan et al., 2021). In hydroponics, plants are supported by inert media such as perlite, coco coir, or rockwool, while their roots are submerged in or exposed to circulating nutrient solutions. Research has shown that hydroponically grown crops can yield up to 30 to 50 percent more than traditional soil-grown crops. This increase is attributed to optimized nutrient absorption and reduced competition from weeds and pests (Dubey & Nain, 2020; Sreedevi & Kumar, 2020). Furthermore, hydroponic systems can be implemented indoors or in urban settings such as rooftops, balconies, or greenhouses, making them ideal for sustainable urban agriculture and indoor gardening. These features position hydroponics as a key strategy for addressing food production challenges in land-limited environments.

Despite its advantages, hydroponic farming requires meticulous control over multiple variables such as temperature, humidity, pH level, electrical conductivity, and nutrient concentration. In manual systems, maintaining these parameters within optimal ranges is labor-intensive, time-consuming, and susceptible to human error. Even minor deviations in these environmental conditions can hinder plant development or lead to crop failure. To overcome these challenges, the integration of Internet of Things (IoT) technologies has been proposed and widely explored in the field of smart agriculture (Surantha, 2019; Shrivastava et al., 2021). IoT systems enable real-time monitoring, automation, and control of agricultural operations using interconnected sensors, actuators, and cloud-based platforms. These technologies help reduce manual labor, lower input costs, and improve yield quality through precision agriculture.

The adoption of microcontrollers such as the NodeMCU ESP8266 and the Arduino Uno has proven effective in the implementation of automated and remotely controlled agricultural systems. NodeMCU offers built-in Wi-Fi capabilities that allow it to transmit sensor data to mobile or cloud applications. In contrast, Arduino Uno provides reliable processing for sensor inputs and control of physical devices such as pumps and valves (Slime et al., 2022; Nugraha et al., 2020). These microcontrollers are programmable, cost-effective, and compatible with a wide range of sensors, including soil moisture, temperature, and humidity sensors. Additionally, IoT platforms such as Blynk and Google Firebase facilitate user interaction through mobile apps,

allowing for real-time data visualization, push notifications, and remote command execution. Studies by Wu et al. (2019) and Kumar et al. (2021) highlight the effectiveness of such platforms in automating irrigation and environmental regulation in both indoor and outdoor farming setups.

Numerous research efforts have demonstrated the efficiency of IoT-based drip irrigation systems, particularly in water management and precision farming (Orakwue et al., 2022; Santosa et al., 2022). These studies report substantial savings in water and labor, along with improvements in crop health and yield. However, most of these implementations have focused on soil-based agriculture (geoponics), and there is a relative lack of studies that specifically tailor IoT automation for hydroponic environments. Furthermore, existing models often rely on single-board controllers and use either SMS-based notification systems or basic web interfaces. These solutions may lack intuitive, user-friendly interfaces and real-time remote control functionalities, which are essential for practical use in modern, urban environments. Systems that utilize only one microcontroller may also be limited in terms of scalability, processing capacity, and integration flexibility for multiple sensors and actuators.

Given these limitations, a significant research gap exists in the development of a hybrid IoT system that integrates both NodeMCU and Arduino Uno in a complementary manner. This approach can leverage the internet connectivity of NodeMCU alongside the robust hardware interfacing capabilities of Arduino Uno. Additionally, incorporating the Blynk IoT mobile application provides a user-friendly graphical interface that enhances system interactivity, accessibility, and real-time control (Radithya et al., 2023). This hybrid configuration is particularly relevant for hydroponic drip irrigation systems, which demand constant monitoring and precise adjustments to environmental conditions. Although the individual technologies are well-documented, comprehensive integration and assessment of such a system tailored specifically for urban or indoor hydroponics remain underexplored in current literature.

Therefore, this study aims to design, develop, and assess an IoT-based automated drip irrigation system tailored for hydroponic farming using an integrated setup of NodeMCU ESP8266 and Arduino Uno. Remote control and monitoring will be facilitated through the Blynk IoT application. The system will utilize sensors to collect real-time data on temperature, humidity, and moisture conditions, which will be used to automate water delivery and maintain ideal growing conditions. Through this study, we aim to contribute a scalable, efficient, and user-centric solution for modern sustainable agriculture, particularly in contexts where land is limited and resource optimization is critical. By addressing the identified technological and practical gaps, this research supports the advancement of smart hydroponic systems and contributes to broader efforts in promoting food security and sustainable urban farming.

Objectives of the Study

The researchers investigated the performance of the devices that were used in hydroponics. This study aimed to determine the functions of an IoT-based drip System with soil moisture, temperature, and humidity sensors in the main hydroponics set. Specifically, it seeks to:

1. Determine the average activation time of the IoT-Based Drip System using the system hardware in terms of system startup, water mode operation, and AI mode operation.
2. Determine the average activation time of the IoT-Based Drip System using the Blynk IoT application in terms of water mode operation and AI mode operation.
3. Measure the average activation time of the AI mode-activated soil moisture sensor when the pump is triggered.
4. Evaluate the sensors' average reaction time, including the soil moisture sensor and the temperature and humidity sensor.
5. Assess whether there is a significant difference in the average activation time of the system between the system hardware and the Blynk IoT application in water mode operation.
6. Assess whether there is a significant difference in the average activation time of the system between the system hardware and the Blynk IoT application in AI mode operation.

II. Methods

Research Design

This study employed a quantitative research method. According to Lucas-Alfieri (2015), quantitative research is a research method that focuses on calculating variables using a graphical procedure, analyzing such measures using a variety of mathematical models, and recording links and comparisons among the variables investigated. The goal of gathering such quantitative data is to identify, explain, and foresee the presence of occurrences, specifically through models and theories. Furthermore, this study will incorporate two specific quantitative research designs: the experimental research design and the descriptive-comparative research design.

Experimental research design is a framework of protocols and procedures created to conduct experimental research with a scientific approach using two sets of variables. The first set of variables is a constant used to measure the differences between the second set (Sunil, 2022). In addition, time is an important factor in establishing a relationship between cause and effect. The experimental design measured the system's performance through time testing. A descriptive-comparative research design aims to

describe the differences between groups without manipulating the independent variable (Cantrell, 2011). A descriptive-comparative research design was used in this study to describe the performance level of the system and examine the differences in the average activation time between the system hardware and the Blynk IoT application.

Pre-Experimental Protocol

The researchers determined the materials needed to actualize the experiment and test it. Most of the materials were purchased online. Moreover, the researchers also visited a hydroponics farm in Tagclucop Strawberry Hills in Bukidnon for observation and sought advice on making the hydroponics system. The researchers purchased sprouts for the lettuce in a local Digos City market.

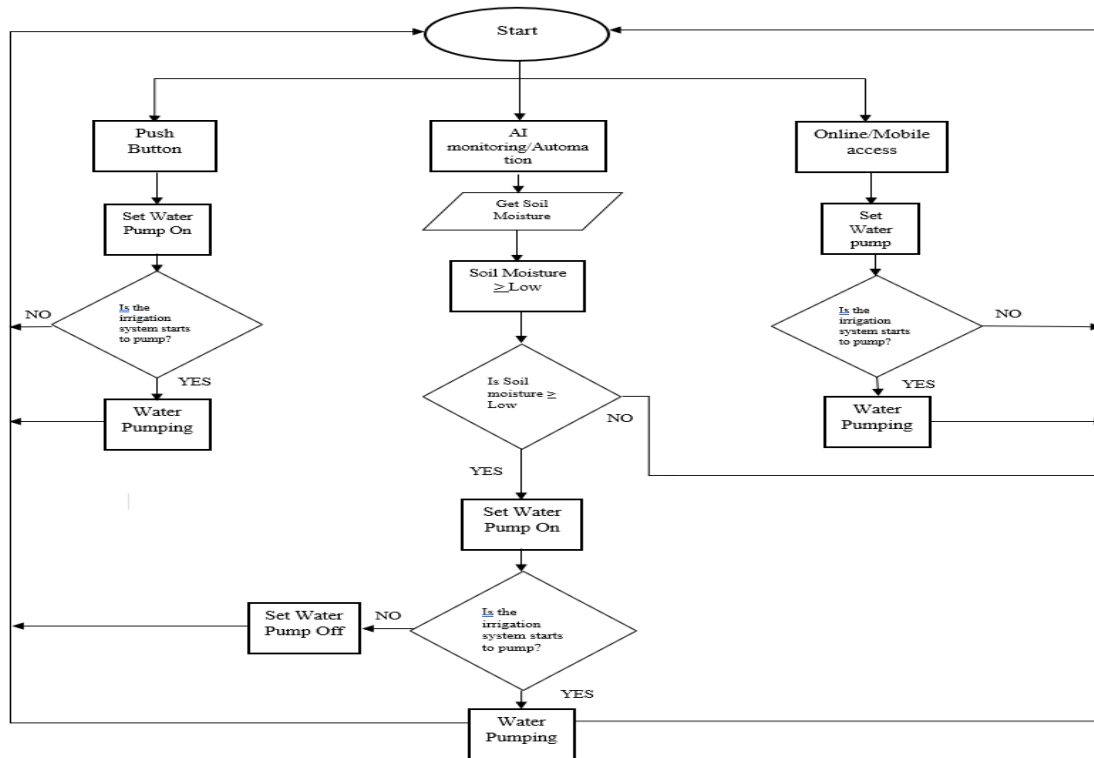


Figure 1. System Flowchart of the Study

After gathering the materials, the construction of the device began. The researchers started constructing the IOT-based drip system type hydroponics, from the program to the project's different physical components. After the building process, the researchers planted the lettuce sprout and tested the hydroponics through time testing to determine the possible conclusions.

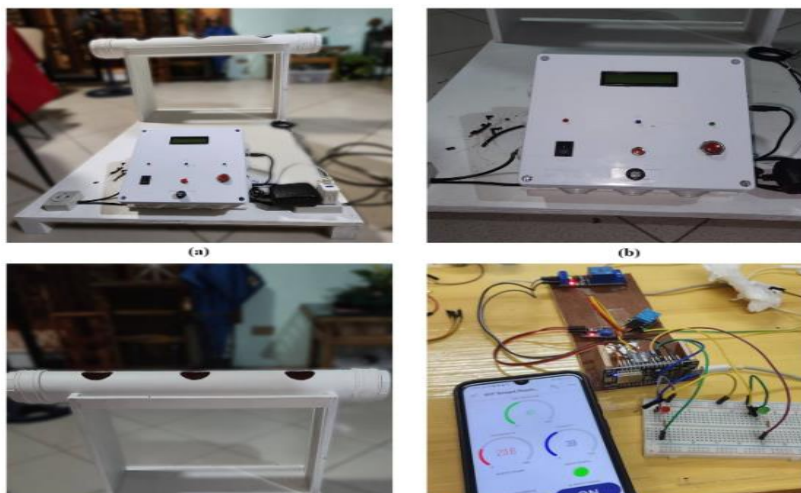


Figure 2. System Design. (a) IoT-based drip system; (b) Device control panel; (c) Growing medium; (d) Blynk IoT

Programming of the Node MCU and Arduino

The applications for both devices to program the Arduino and Node MCU are used. The programming codes went through monitoring and reviewing, and the researchers asked for help from experts for consultation and clarifications concerning the

coding of the Arduino. Other structured source codes are modified and serve as references. The projected output is to set a conditional automatic activation of the water pump, which is the irrigation system's main part. The soil moisture sensor has been programmed to follow specific conditions for monitoring and automatic activation of the system.

Table 1. Table of Interpretation to Determine the Level of Soil Moisture in the System

Percentage	Descriptive Reading	Interpretation
0-40%	Low Moisture	This means that the moisture of the cocopeat is below normal.
41-60%	Normal Moisture	This means that the moisture of the cocopeat is in the normal range.
61-100%	High Moisture	This means that the moisture of the cocopeat is above normal.

The soil moisture percentages will be displayed in the system's LCD and the application. At the same time, the descriptive reading will be responsible for activating the water pump (in AI mode) when specific conditions are met. Moreover, the AI mode RGB light of the system has been programmed to show green if the moisture is at the optimum level or a higher moisture and blue if the soil moisture is below normal.

Table 2. Table of Conditions for Activating the System's Water Pump in AI mode

Conditions	Interpretation
Low Soil Moisture (0-40%)	The water pump will be activated until it reaches 41-60% moisture. The blue LED will light up.
Normal Soil Moisture (41%-60%)	The water pump will not be activated as the soil moisture is optimum. The green LED will light up.
High Moisture (61%-100%)	The water pump will not be activated and/or will stop as it reaches the desired amount of moisture. The green LED will light up.

Hardware Implementation

The hardware implementation of this study involves the attachment and configuration of physical components essential for both the hydroponic system and the IoT-based irrigation system. The IoT setup includes the materials necessary to operate the automatic irrigation system, with all boards, modules, and wiring securely housed inside a PVC box for protection and organization. The hydroponic setup is designed to support the efficient growth of lettuce by distributing water through a network of PVC pipes with compartments and water lining. A water pump circulates water throughout the system to irrigate the lettuce, while an integrated overflow mechanism helps regulate the water volume within the compartments to avoid excess accumulation.

To enable automation, the Node MCU is connected to the Arduino microcontroller using jumper wires that follow the correct pin configuration. This connection facilitates communication between components for efficient system control. The DHT11 temperature and humidity sensors are also connected to the Node MCU through male-to-female jumper cables, allowing real-time monitoring of environmental conditions. Likewise, a relay module is connected to the Arduino to manage high-voltage operations using jumper connections. For all electrical configurations and wiring connections, the researchers consulted with professionals to ensure the system's accuracy, safety, and proper functionality.

Testing the Device

In testing the device, the researchers used the time testing method to determine how functional the system is. Each experiment consists of 50 trials, with a total of 400 trials. It specifically determined the eight aspects of the project: (1) to test the activation time when starting the system, to test the activation time in (2) water operation mode and (3) AI operation mode using the system hardware, to test the activation time in (4) water operation mode and (5) AI operation mode using the Blynk IoT app (6) to test the activation time of the water pump when the AI mode-activated soil moisture sensor interprets it and to test the reaction time of the (7) soil moisture and (8) temperature and humidity sensors. Moreover, each trial was executed using a stopwatch with a millisecond reading for efficient data collection. This determined the mean time interval when the system activates, and sensors react as the timer stops.

Data Analysis

A statistician was consulted to ensure accurate and efficient data analysis. This study aimed to (1) determine the average activation time of the system using hardware and the Blynk IoT application, (2) measure the reaction time of the soil moisture, temperature, and humidity sensors, and (3) compare activation times between hardware and Blynk in both water and AI modes. The mean and standard deviation were used to evaluate activation and reaction times based on 50 trials. An independent samples t-test was applied to identify significant differences between hardware and Blynk activation times. A p-value of ≤ 0.05 indicated a significant difference, while a p-value > 0.05 indicated no significant difference (Frost, 2023).

III. Results and Discussion

Activation Time of the IoT-Based Drip System Using System Hardware

Table 3 shows the activation time of the IoT-Based Drip System using System Hardware. It shows that the average activation time for system startup is 7.41 seconds with a standard deviation of 1.40 seconds, which means that the device is fully functional. The data points are clustered around the mean. Therefore, the data are close to the average activation for system startup. In terms of water mode operation, the average activation time of the system is 0.32 seconds with a standard deviation of 0.14 seconds, which indicates that the data are close to its average activation. Meanwhile, the system averages 1.80 seconds with a standard deviation of 0.22 seconds in AI mode operation. This suggests that the data has a consistent/approximate 1.80 seconds of activation time due to its standard deviation of 0.22 seconds.

Table 3. Activation Time of the IoT-Based Drip System Using System Hardware

	Trials	Mean	SD
System Startup	50	7.41	1.40
Water Mode Operation	50	0.32	0.14
AI Mode Operation	50	1.80	0.22

Activation Time of the IoT-Based Drip System Using Blynk IoT Application

Table 4 shows the activation time of the IoT-Based Drip System using the Blynk IoT Application. It shows that the average activation time for water mode operation is 0.56 seconds with a standard deviation of 0.34 seconds. This means the data are close to the average time in activating the water mode operation. Meanwhile, the system has an average of 2.13 seconds with a standard deviation of 0.26 seconds in terms of AI mode operation, which suggests that the range of data is close to the mean average of activation.

The results of this study about the water mode operation contradict the study of Nugraha et al. (2020), which revealed that using a smartphone application such as Google Firebase takes 3 seconds for the DC water pump to flow the water. Compared to the study of Nugraha et al. (2020), the water mode operation in this study is more efficient because it takes only 0.56 seconds to start the drip irrigation of the water mode operation using the Blynk IoT application.

Table 4. Activation Time of the IoT-Based Drip System Using Blynk IoT Application

	Trials	Mean	SD
Water Mode Operation	50	0.56	0.34
AI Mode Operation	50	2.13	0.26

Activation Time of the AI Mode-Activated Soil Moisture Sensor with Pump

Table 5 shows the activation time of the AI Mode-Activated Soil Moisture Sensor with the Pump. It shows that the average activation time for the AI Mode-Activated Soil Moisture Sensor is 2.41 seconds with a standard deviation of 0.65 seconds, which means that the data is close to the average time for activating the water mode operation.

Table 5. Activation Time of the AI Mode-Activated Soil Moisture Sensor with Pump

	Trials	Mean	SD
AI Mode-Activated Soil Moisture Sensor	50	2.41	0.65

This finding contradicts the statement of Santosa et al. (2022), who state that the water pump irrigates after 1 minute according to the soil moisture sensor readings and when its readings are in low-level moisture. The AI Mode-Activated Soil Moisture Sensor in this study only takes 2.41 seconds to start its function, concluding that it is more productive since the study by Santosa et al. (2022) takes at least 1 minute to operate.

Efficiency of Soil Moisture and Temperature/Humidity Sensors

Table 6 shows the Efficiency of the Soil Moisture Sensor. It shows that the average activation of reaction time is 0.37 seconds with a standard deviation of 0.13 seconds, which means that data in reading soil moisture are close to the average reaction time. This also suggests that the Soil Moisture sensor efficiently reads data in real time. Regarding the temperature of the humidity sensor, the average activation time of the system is 6.37 seconds with a standard deviation of 1.91 seconds, indicating that the sensor for temperature and humidity is efficient due to its reaction to reading data in real-time.

Table 6. Efficiency of Soil Moisture and Temperature/Humidity Sensors

	Trials	Mean	SD
Soil Moisture Sensor	50	0.37	0.13
Temperature of Humidity Sensor	50	6.37	1.91

The findings about the efficiency of the soil moisture sensor contradict the study of Adetia et al. (2022), stating that the soil moisture sensor activates at 1 second during the retrieval process and sends data to both system hardware and the Blynk application. Moreover, this finding does not support the study of Jain et al. (2020), which revealed that soil moisture sensors can collect the moisture level in the plants' soil within 2 seconds. As a result, the soil moisture sensors in this study are more efficient than other studies, considering that it only takes 0.37 seconds to read the soil's moisture level. In terms of temperature and humidity sensors, the results in this study contradict the findings of Orakwue et al. (2022), stating that within 2 seconds, the temperature and humidity sensor receives and shows new data. Also, this study does not support the findings of Santosa et al. (2022), who stated that the sensor's temperature and humidity have an average result of showing its readings every minute for an hour.

Significance of the Difference Between Water Mode Operations Using System Hardware and Using Blynk IoT Application

Table 7 shows the independent samples t-test results to determine the significance of the difference between the water mode operations using system hardware and the Blynk IoT App. It can be observed that the t value is -4.56, with 98 degrees of freedom. The p-value is 0.000, which is less than 0.05. This further means that the null hypothesis should be rejected. This indicates a significant difference in the water mode operations of system hardware and the Blynk IoT App. This suggests that the System Hardware and the Blynk IoT app significantly differ in operation. Furthermore, since the system hardware takes less time than the Blynk IoT app, this suggests that the system hardware is faster than the Blynk IoT app regarding water mode operation.

Table 7. Significance of the Difference Between Water Mode Operation Using System Hardware and Using Blynk IoT Application

	Trials	Mean	SD	t	df	p	Decision
System Hardware	50	0.32	0.14	-4.56	98	0.000	Reject H_0
Blynk IoT App	50	0.56	0.34				(Significant)

Significance of the Difference Between AI Mode Operations Using System Hardware and Using Blynk IoT Application

Table 8 shows the independent samples t-test results to determine the significance of the difference between the AI mode operations using system hardware and the Blynk IoT App. It can be observed that the t value is -6.65, with 98 degrees of freedom. The p-value is 0.000, which is less than 0.05. This further means that the null hypothesis should be rejected. This indicates a significant difference in the AI mode operations of system hardware and the Blynk IoT App. As shown in Table 6, the system hardware has a 1.80 mean average with a 0.22 standard deviation, while the Blynk IoT App has a 2.13 mean average with a standard deviation of 0.26; this suggests that the System Hardware is better and more efficient than the Blynk IoT in terms of the AI mode operation.

Table 8. Significance of the Difference Between AI Mode Operations Using System Hardware and Using Blynk IoT Application

	Trials	Mean	SD	t	df	p	Decision
System Hardware	50	1.80	0.22	-6.65	98	0.000	Reject H_0
Blynk IoT App	50	2.13	0.26				(Significant)

The results of this study about the significant difference between water mode and AI mode operation using the system hardware and Blynk IoT application contradicts the findings of Chen et al. (2019), which revealed that Blynk applications have only less than 0.2 seconds of delay in sending the information of the sensors to a mobile phone. Thus, this implies that the system hardware performs better than the Blynk IoT app. However, Nugraha et al. (2020) stated that controlling the IoT-based drip system through a smartphone application depends on Internet Service Providers' (ISPs) speed.

IV. Conclusions

This study developed an automated hydroponic drip irrigation system using Arduino UNO and Node MCU to evaluate activation and reaction times. Results showed that the system operated efficiently, particularly in water and AI modes, using the Blynk IoT app, with faster activation times than reported in related studies. The soil moisture sensor also demonstrated quick response times. However, the temperature and humidity sensors reacted slower than some existing systems. Significant differences were found between the performance of the system hardware and the Blynk application. While some components outperformed previous designs, further research is needed to assess overall efficiency, especially due to limited studies combining Arduino UNO and Node MCU modules. These findings offer a basis for enhancing IoT-based hydroponic systems in future work.

V. Recommendations

The researchers recommend that the Department of Agriculture adopt this study's findings to benefit farmers and plant owners, as the automated hydroponic system can save time, effort, space, and resources compared to traditional planting methods. Urban gardeners with internet access should consider using smartphones for digital control and monitoring of their hydroponic systems, as this approach offers greater convenience than hardware-based control, as demonstrated in the study. While only temperature and soil moisture sensors were incorporated in this study, future researchers should include sensors for monitoring water pH levels and to explore more accurate soil moisture readings. To enhance the accessibility of the Blynk IoT application, future studies should consider using high-range WiFi modems, as a shorter range limited this study. Additionally, future researchers are advised to experiment with different growing mediums, as the study used only coco peat, to assess whether there are significant differences in moisture readings across various mediums.

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