

Bridging Agriculture and Engineering Through an IoT-Based Scalable Pinakbet Garden Platform

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ABSTRACT

This study designed, developed, and evaluated an Internet of Things (IoT)-based scalable Pinakbet Garden Platform that integrates agricultural requirements with engineering automation for smart vegetable production. The platform supports the cultivation of Pinakbet crops, including eggplant, bitter melon, squash, okra, and string beans, through distributed Wemos D1 Mini sensor nodes, a Raspberry Pi local server, MQTT-based communication, and a web-based monitoring and control dashboard. Using a design and development research approach with experimental validation, the study compared traditional manual irrigation with IoT-based automated irrigation over one complete crop cycle. Environmental data on soil moisture, temperature, humidity, and light intensity were collected at five-minute intervals, while plant height, leaf count, flowering time, yield, response time, packet loss, signal strength, server load, and scalability indicators were monitored. Findings showed that the system operated continuously with stable real-time monitoring, average response from threshold detection to pump activation of approximately 1-3 seconds, and a total average response cycle of 2.7 seconds. The IoT group recorded higher final plant height (74.2 cm vs. 68.4 cm), greater leaf count (49 vs. 42), and higher average yield per plant (2.14 kg vs. 1.85 kg), equivalent to approximately 15.68% yield improvement. Scalability testing from one to five nodes showed packet loss below 5%, latency increase within the acceptable limit, and Raspberry Pi CPU utilization below 80%. The study concludes that the IoT-based Pinakbet Garden Platform is a cost-effective, scalable, and locally deployable smart farming model that can improve irrigation efficiency, crop monitoring, and sustainable vegetable production.

Keywords: *automated irrigation, Internet of Things, Pinakbet crops, precision farming, scalable platform, smart agriculture*

INTRODUCTION

Agriculture remains central to food security, local livelihoods, and community development in the Philippines, where vegetable production supports household consumption and local markets. Pinakbet crops such as eggplant, bitter melon, squash, okra, tomato, and string beans are culturally important and commonly cultivated in small gardens and community farms. However, small-scale production faces persistent constraints, including inefficient irrigation, resource limitations, climate variability, and limited access to real-time monitoring technologies. These conditions make it difficult for growers to maintain consistent soil moisture and environmental conditions needed for healthy crop growth.

Smart agriculture offers a practical response to these challenges by using sensors, microcontrollers, networked communication, and automated control systems to support data-driven farm management. The Internet

of Things (IoT) enables continuous monitoring of soil moisture, temperature, humidity, and light intensity, while embedded automation allows irrigation and related farm operations to respond to actual environmental conditions rather than fixed schedules. In this way, IoT-based systems can improve water-use efficiency, reduce manual labor, and provide timely information for decision-making in vegetable production.

This study therefore developed and evaluated an IoT-based scalable Pinakbet Garden Platform that bridges agriculture and engineering. The system utilized Wemos D1 Mini sensor nodes, a Raspberry Pi local server, MQTT communication, and a web-based monitoring dashboard to automate irrigation and monitor environmental conditions. Unlike cloud-dependent systems, the local server design was intended to reduce latency, support offline functionality, and maintain reliability in locations with unstable internet connectivity. The study assessed functionality, water-use efficiency, crop performance, network scalability, and system response time to determine whether the platform can serve as a cost-effective and scalable model for sustainable smart farming in the Philippine context.

Literature Review

IoT and Precision Agriculture

The expansion of IoT in agriculture has transformed conventional farm monitoring into a data-driven process. IoT technologies enable farms to gather information from distributed sensors, process data through local or cloud platforms, and trigger automated responses based on measurable environmental conditions (Da Xu et al., 2014; Tzounis et al., 2017). In agriculture, such systems support precision farming by allowing producers to make decisions based on soil, crop, and climate data rather than manual observation alone (Ayaz et al., 2019; Khanna & Kaur, 2019).

Smart farming platforms are particularly relevant in resource-constrained settings because they can improve the efficiency of water, labor, and input use. Elijah et al. (2018) emphasized the role of IoT and data analytics in addressing agricultural monitoring challenges, while Wolfert et al. (2017) argued that data-driven smart farming enhances decision-making through more accurate and timely information. For small-scale vegetable production, these capabilities are important because crop performance is highly sensitive to soil moisture, temperature, and environmental fluctuations.

Embedded Systems, Local Servers, and Communication Protocols

Embedded systems provide the technical foundation of low-cost smart agriculture platforms. Microcontrollers and sensor nodes enable localized collection of soil moisture, temperature, humidity, and light intensity data, while gateways such as Raspberry Pi units can process, store, and visualize information. The use of local servers is significant because it can reduce dependence on unstable internet connectivity and provide faster response for automation tasks, a design issue also recognized in edge and cloud computing approaches for smart farming (Zamora-Izquierdo et al., 2019).

Communication protocols are equally important in maintaining system reliability. MQTT is widely used in IoT systems because it supports lightweight publish-subscribe communication suitable for low-bandwidth sensor networks (Banks & Gupta, 2014). Related work on wireless sensor networks and agriculture confirms that efficient communication architecture contributes to the accuracy, scalability, and timeliness of farm monitoring systems (Gutierrez et al., 2014; Ndi et al., 2018). In the present platform, MQTT communication between Wemos D1 Mini nodes and the Raspberry Pi server supported real-time data transfer and automated irrigation control.

Automated Irrigation and Sustainable Vegetable Production

Automated irrigation systems respond to actual soil or crop conditions rather than relying on fixed watering schedules. Prior research on wireless sensor networks and GPRS-based irrigation showed that automated control can support more efficient use of water and improve field decision-making (Gutierrez et al., 2014). Patil and Biradar (2019) similarly highlighted the value of IoT-based smart agriculture monitoring systems in improving the visibility of field conditions and supporting timely action.

The connection between sensor-based monitoring and crop performance is also supported by broader work on smart farming and machine learning in agriculture. Liakos et al. (2018) reported that data-oriented agricultural technologies can improve production decisions, while Kamilaris and Prenafeta-Boldú (2018) discussed the potential of advanced analytics for crop and farm management. For vegetable gardens, maintaining soil moisture within suitable ranges can reduce plant stress, improve leaf development, and contribute to more stable yield outcomes. This supports the use of automated irrigation in Pinakbet crop production.

Scalability, Reliability, and Interdisciplinary Learning

A scalable smart agriculture platform must accommodate additional sensor nodes without major redesign of hardware, communication, or data processing components. Wireless sensor network studies show that scalability, packet loss, latency, and server load are important criteria in evaluating whether a system can expand from a prototype to a larger deployment (Ojha et al., 2015; Zamora-Izquierdo et al., 2019). The present study therefore tested incremental node expansion from one to five nodes and monitored packet loss, latency, CPU utilization, and memory use.

The Pinakbet Garden Platform also has educational and interdisciplinary value because it connects agricultural production with electronics, programming, data visualization, and systems design. Rayes and Salam (2019) described IoT as a pathway from digital promise to practical systems, while Wolfert et al. (2017) emphasized that smart farming requires collaboration across technical and agricultural domains. In this sense, the platform is not only a farm automation tool but also a model for interdisciplinary learning and locally deployable innovation in sustainable agriculture.

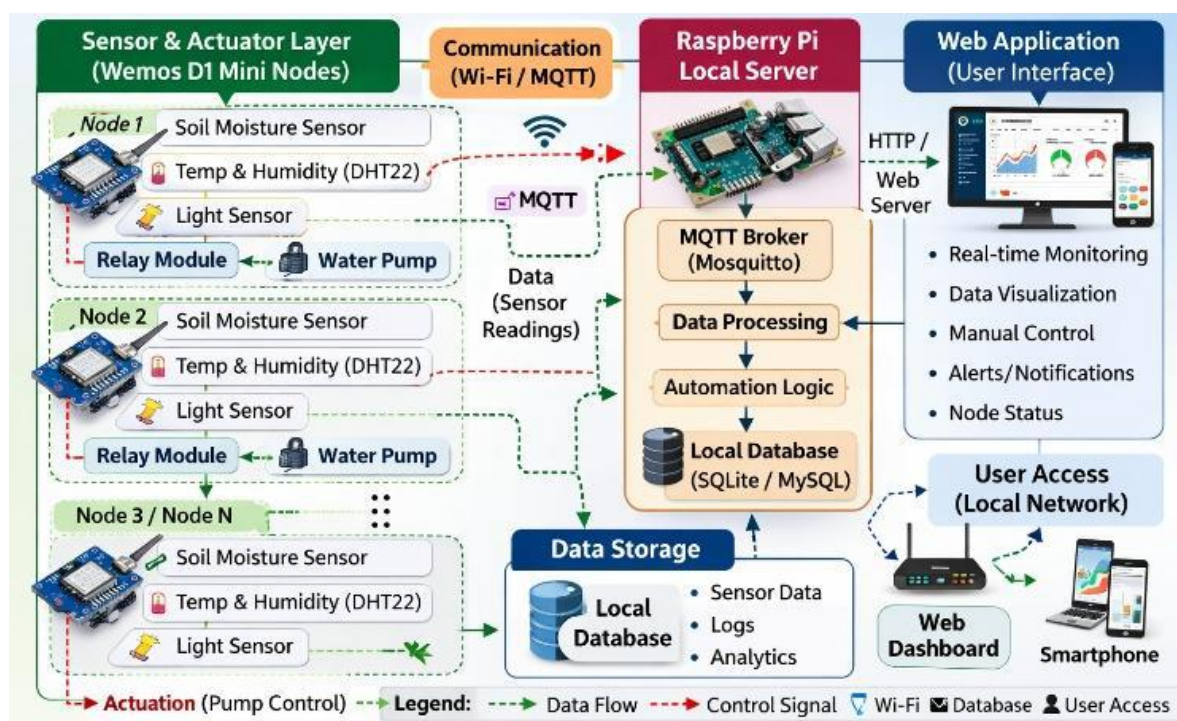


Figure 1. *Conceptual Framework/System Architecture of the IoT-Based Scalable Pinakbet Garden Platform*

METHODS

Research Design

The study applied a design and development research approach with experimental validation. This design was appropriate because the study focused on developing an IoT-based scalable Pinakbet Garden Platform, validating its functionality, and comparing its performance with traditional manual irrigation. Agricultural parameters were aligned with system design through a concurrent engineering approach so that crop needs and technical automation requirements informed each other.

Research Locale and Experimental Setup

The system was developed for small-scale Pinakbet crop cultivation using garden beds configured for both manual and IoT-based irrigation. The study focused on vegetables commonly associated with Pinakbet, including eggplant, bitter melon, squash, okra, and string beans. The experiment covered one complete crop cycle of approximately 60 to 90 days. Similar environmental conditions were maintained for the control and experimental groups to allow comparison of plant growth and system performance.

Materials, System Architecture, and Hardware Components

The platform used a modular star-topology architecture in which multiple Wemos D1 Mini sensor nodes communicated with a centralized Raspberry Pi local server. Each sensor node monitored soil moisture, temperature, humidity, and light intensity. The sensor node also controlled a relay module and water pump to automate irrigation. The Raspberry Pi functioned as MQTT broker, local database host, web server, and data processing unit.

Table 1. *Summary of System Components and Functions*

Component	Specification/Element	Function
Sensor node	Wemos D1 Mini (ESP8266)	Collected environmental data and communicated with the local server
Soil monitoring	Capacitive soil moisture sensor	Measured soil moisture and triggered irrigation decisions
Climate monitoring	DHT22 temperature and humidity sensor	Recorded environmental temperature and humidity
Light monitoring	Light intensity sensor	Measured available light for crop monitoring
Actuation	Relay module and water pump	Automated irrigation when soil moisture was below threshold
Gateway/server	Raspberry Pi with MQTT, database, and web server	Processed data, hosted the dashboard, and stored records

Software, Communication, and Automation Logic

MQTT communication was implemented for lightweight and reliable data exchange between the Wemos D1 Mini nodes and the Raspberry Pi server. The sensor nodes published environmental data, while the Raspberry Pi subscribed to and stored data in the local database. Control commands were transmitted back to the nodes when irrigation activation or manual override was required. The web application provided real-time monitoring, historical data graphs, manual irrigation override, node status indicators, and alert notifications.

The irrigation automation algorithm was based on a simple threshold rule. If soil moisture fell below the configured threshold, the pump was activated; otherwise, the system remained on standby. This decision logic allowed irrigation to respond to the real-time needs of the crops rather than a fixed schedule. The local-server design also supported offline functionality and reduced latency compared with fully cloud-dependent approaches.



Figure 2. Methodology Flow Diagram of the IoT-Based Scalable Pinakbet Garden Platform

Data Gathering Procedure

The study collected environmental data every five minutes, including soil moisture percentage, temperature in degrees Celsius, humidity percentage, and light intensity in lux. Agricultural performance data were collected weekly, including plant height, leaf count, flowering time, and yield weight in kilograms. System performance data were also collected, including response time, packet loss rate, received signal strength indicator, and server load.

Table 2. Experimental Deployment and Data Collection Design

Group/Metric	Description
Control group	Pinakbet garden beds managed through manual irrigation
Experimental group	Pinakbet garden beds managed through IoT-based automated irrigation
Crop cycle	One complete crop cycle lasting approximately 60-90 days
Environmental data interval	Every five minutes
Agricultural data interval	Weekly measurement of plant growth and yield indicators
Scalability testing	Incremental sensor node expansion from 1 to 5 nodes

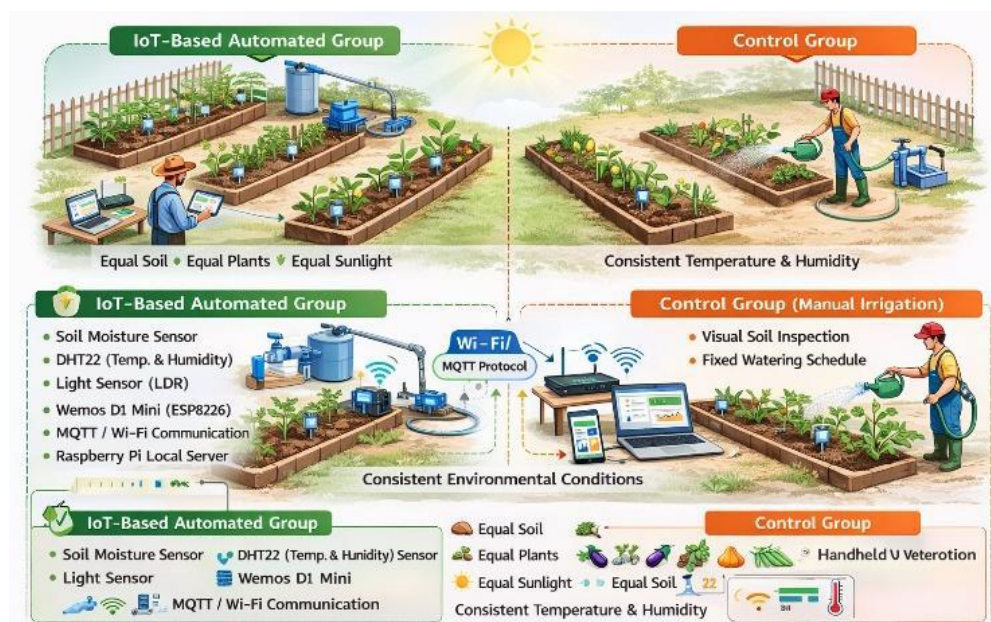


Figure 3. *Experimental Deployment Setup for Control and IoT-Based Automated Garden Beds*

Data Analysis

The analysis used descriptive statistics to summarize environmental parameters, plant growth indicators, yield performance, network latency, packet loss, CPU utilization, RAM utilization, and response time. The yield difference between the control and IoT groups was interpreted using the reported percentage increase. Scalability was considered successful when packet loss remained below 5%, latency increase remained below 15%, and Raspberry Pi CPU use stayed below 80%.

Ethical Consideration

The study involved system testing and crop monitoring rather than sensitive human-subject data collection. The researchers conducted the experiment in a controlled garden setting and used the results only for academic and system-development purposes. The system was designed to promote safe, efficient, and sustainable agricultural practice. Acknowledgment was given to Pampanga State Agricultural University Administration and the Research, Innovation and Extension Training Office for supporting the research.

RESULTS AND DISCUSSION

System Functionality and Web-Based Monitoring

The IoT-based garden system was successfully deployed and operated continuously during the crop growth cycle. The Wemos D1 Mini sensor nodes collected soil moisture, temperature, humidity, and light intensity data at five-minute intervals and transmitted them to the Raspberry Pi local server through Wi-Fi using MQTT. The server stored incoming data in a local database and hosted the web application without prolonged downtime or system crashes. The dashboard displayed real-time environmental conditions, irrigation status, and historical trends, while the manual override function allowed users to activate or deactivate irrigation within the local network.

The system response from threshold detection to pump activation was approximately 1-3 seconds, showing efficient communication between the sensor nodes and the local server. This near real-time behavior is important for automated irrigation because delayed activation can reduce the effectiveness of soil-moisture management, especially when crop beds are exposed to changing heat and light conditions.

Environmental Monitoring Performance

The environmental monitoring results showed that the IoT system produced stable and reliable readings. Soil moisture readings were consistent after calibration, while temperature and humidity followed expected daily changes. The automated irrigation system activated whenever soil moisture fell below the configured threshold, keeping the moisture level within the optimal range for Pinakbet crops most of the time. This outcome demonstrates that real-time sensing and automated control improved irrigation accuracy and consistency compared with manual watering.

Table 3. *Average Environmental Parameters in the Experimental Group*

Parameter	Minimum	Maximum	Mean	Standard Deviation
Soil moisture (%)	42	78	60.35	8.12
Temperature (°C)	25.4	34.8	29.76	2.41
Humidity (%)	58	86	71.42	6.37
Light intensity (lux)	8,500	42,300	24,150	7,980

The mean soil moisture of 60.35% indicates that the system generally maintained soil moisture within the target range of 55-70%. This is a key result because the platform was designed to reduce irregular watering and maintain more suitable growing conditions for vegetable crops. The relatively stable environmental data also validate the use of embedded sensors as practical inputs for crop-management decisions.

Plant Growth and Yield Performance

The experimental group using IoT-based automated irrigation demonstrated more uniform growth compared with the manually irrigated control group. Plants in the automated group showed fewer signs of water stress, such as wilting or delayed flowering. At the final week of measurement, the IoT group recorded a higher average plant height, greater leaf count, and higher average yield per plant. These results suggest that maintaining soil moisture through automated irrigation contributed positively to plant development and harvest output.

Table 4. *Plant Growth and Yield Comparison at Final Week Measurement*

Parameter	Control Group	IoT Group
Average plant height (cm)	68.4	74.2
Average leaf count	42	49
Average yield per plant (kg)	1.85	2.14

The IoT-based system improved average yield by approximately 15.68%. This improvement supports the claim that automated irrigation can contribute to crop productivity when it reduces moisture fluctuations and responds to crop needs more consistently than manual irrigation. Although the source manuscript described the increase as marginal, it was also reported as statistically significant at the chosen confidence level, supporting the effectiveness of the automated system in improving crop productivity.

Scalability and System Reliability

Scalability testing was conducted by incrementally increasing the number of Wemos D1 Mini sensor nodes from one to five. The system remained within the criteria set for successful scalability: packet loss stayed below 5%, latency increase remained acceptable, and Raspberry Pi CPU use stayed below 80%. These findings indicate that the modular star-topology design can support additional sensor nodes without major degradation in system performance.

Table 5. *System Scalability Testing Results*

Number of Nodes	Average Latency (sec)	Packet Loss (%)	CPU Usage (%)	RAM Usage (%)
1 node	1.2	0.8	32	41
3 nodes	1.5	2.1	54	56
5 nodes	1.8	4.3	73	68

Latency increased by only 0.6 seconds from one to five nodes, while packet loss remained at 4.3% even at five nodes. CPU utilization reached 73% and RAM usage reached 68%, both within acceptable operating limits. These results confirm that the local server could handle multiple nodes and database updates without instability, supporting the platform's potential expansion from a small backyard garden to larger community or institutional deployments.

System Response Time and Practical Implications

Table 6. *System Response Time*

Event	Mean Response Time (sec)
Soil moisture threshold detection	0.8
Pump activation delay	1.1
Dashboard update	1.6

The total average response cycle was 2.7 seconds, confirming near real-time operation. This rapid response is important because the usefulness of an automated irrigation platform depends on its ability to detect soil-moisture changes, activate the pump, and update the user interface quickly. The dashboard also supported data-driven decision-making by allowing users to view real-time values and historical trends through smartphones and laptops connected to the same local network.

Overall, the results validate the platform as an effective integration of embedded systems and agricultural practice. The system improved irrigation consistency, supported crop monitoring, increased yield, and demonstrated modular scalability. Its local-server architecture also makes it practical for areas with unstable internet connectivity, which is relevant in many small-scale agricultural settings.

CONCLUSION

The study concluded that the IoT-based scalable Pinakbet Garden Platform successfully integrated Wemos D1 Mini sensor nodes, a Raspberry Pi local server, MQTT communication, and a web-based monitoring and control system to support smart vegetable production. The system automated irrigation using real-time soil-moisture data and provided continuous monitoring of temperature, humidity, and light intensity. Its local-server architecture enhanced reliability, reduced latency, and enabled operation without full dependence on cloud connectivity.

The findings showed that the IoT-enabled garden beds maintained more stable soil moisture, supported better plant growth, and produced a higher average yield than manually irrigated beds. The IoT group recorded a 15.68% yield increase, higher final plant height, and greater leaf count. Scalability testing also confirmed that the system could support multiple nodes while keeping packet loss below 5%, CPU usage below 80%, and response times within near real-time limits. These results demonstrate that the platform is a cost-effective, modular, and scalable model for improving efficiency and sustainability in small-scale vegetable farming.

Recommendation

Future development of the Pinakbet Garden Platform should include additional sensors such as soil pH, nutrient-level sensors, and crop-health indicators to provide a more complete basis for decision-making. The integration of machine learning may also be explored to support predictive irrigation, early disease detection, and yield forecasting. Such improvements can increase the intelligence of the platform and make it more responsive to crop-specific needs.

Hybrid local-cloud architectures are also recommended to enhance accessibility while preserving the reliability benefits of local processing. The system may be tested over longer planting cycles, different seasons, and wider field conditions to validate its performance under diverse environmental situations. Collaboration with local farmers, agricultural extension workers, and schools may further support adoption, training, and

interdisciplinary learning in smart agriculture. Finally, the platform should be refined for larger community or institutional farms to evaluate cost, maintenance requirements, user experience, and long-term sustainability.

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