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IoT-based Soil Nutrient Monitoring and Control Using Fuzzy Logic and Multi-Modal Sensor Integration

Andi Wahyunita Hakis [1]*, Abdul Latief Arda [2]*, Abdul Jalil [3]**
* Department of Computer Systems, Handayani University Makassar, Makassar
** Department of Computer and Network Engineering, State Polytechnic of Ujung Pandang, Makassar
mail1@polibatam.ac.id [1], abdullatief@handayani.ac.id [2*], abduljalil@poliupg.ac.id [3]

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ABSTRACT

The decline in soil quality due to inappropriate agricultural practices has become one of the main factors contributing to reduced agricultural productivity. The primary focus of this research is on monitoring and controlling soil nutrient quality, particularly in clay soil used for chili cultivation. This study aims to develop an Internet of Things (IoT)-based monitoring system integrated with multi-modal sensors and fuzzy logic algorithms. The system is designed to support precision agriculture by enabling automated decision-making based on real-time environmental data. The research uses an experimental approach, involving the design of a system based on the ESP32 microcontroller, sensor data processing using the Mamdani fuzzy algorithm, and integration with the Blynk platform for remote monitoring and control. The system responds to changes in environmental conditions to determine optimal timing for irrigation and liquid nutrient application adaptively. The test results show that the system achieved a classification accuracy of 84% and an average F1-score of 88.5%, indicating its effectiveness in handling continuous and uncertain sensor data. Evaluation of the fuzzy logic performance revealed a 75.8% success rate in irrigation control and 99.8% accuracy in nutrient delivery, demonstrating the system's ability to respond accurately and efficiently to actual soil and environmental conditions. With its stable, adaptive, and resource-efficient performance, this system has the potential to become a practical solution for automating irrigation and fertilization processes in support of technology-driven and sustainable agriculture.

I. INTRODUCTION

Monitoring the quality of soil nutrients is a vital aspect of precision agriculture, aiming to increase crop yields and maintain long-term soil fertility. Healthy soil contains a balanced composition of macronutrients (such as nitrogen, phosphorus, and potassium) and micronutrients (such as iron, manganese, and copper). A deficiency or excess of any of these nutrients can negatively affect plant growth. Technology-based monitoring systems provide real-time information that enables more effective and timely decisions in agricultural management [1] [8].Agriculture is a vital sector in meeting global food demands, yet it faces increasing challenges due to population growth, climate change, and land degradation. One of the most pressing issues is the decline in soil quality, which significantly impacts plant productivity. Poor soil quality, especially in terms of nutrient content, is a major contributor to reduced crop yields. Nutrient imbalance in soil can lead to suboptimal plant growth, inefficient fertilizer usage, and ultimately, economic losses for farmers [2] [9].

High-quality soil contributes to improved crop yields, economic welfare for farming communities, and resistance to erosion. It also reduces health risks associated with heavy metal contamination. Soil quality is closely linked to environmental sustainability—not merely as a growing medium but as a key factor in environmental and ecosystem function. Inappropriate land management practices often reduce soil productivity and indicate that the soil is no longer functioning as intended. This dysfunction leads to continued degradation of soil quality [3] [10].

The decline in soil productivity does not only result in lower yields, but also raises agricultural production costs, weakens food security, and damages surrounding ecosystems. These negative effects are particularly severe in regions highly dependent on agriculture for livelihoods. Improper agricultural practices—such as excessive tillage, overuse of heavy machinery, imbalanced use of synthetic fertilizers, poor irrigation and water management, overuse of pesticides, low organic input, and poor crop rotation planning—worsen soil degradation. These issues also lead to economic, social, and health consequences, such as food insecurity, reduced farmer income, poverty, and deteriorating water quality affecting public health [4] [11] [13].

The application of Blynk and fuzzy-based control systems in chili cultivation on clay soil is expected to provide significant economic and productivity benefits. By enabling precise monitoring of soil moisture, nutrients, and environmental conditions, farmers can optimize irrigation and fertilizer use, which reduces unnecessary input costs while maintaining ideal growing conditions. This leads to healthier plants, lower risk of crop failure, and higher yields. In addition, automation through Blynk reduces the need for constant field supervision, saving labor costs and time. With improved productivity and efficiency, farmers can achieve greater profits, enhance the quality of chili harvests, and strengthen their competitiveness in the agricultural market. Overall, this technology contributes to more sustainable and cost-effective chili farming.

In practice, soil quality assessment is still mostly performed manually, requiring considerable time, labor, and cost. Conventional methods have limitations, including low accuracy and an inability to provide real-time data. As a result, farmers struggle to make fast and accurate decisions for soil management. Manual techniques also fail to detect dynamic changes in soil conditions, often delaying corrective actions and reducing agricultural productivity.

Previous studies on soil nutrient monitoring and control systems have shown several shortcomings. Most focus solely on basic parameters such as soil pH and moisture, without incorporating a more comprehensive view of macro- and micronutrient levels. Additionally, many systems lack the ability to automatically analyze sensor data and generate adaptive fertilization recommendations using fuzzy logic [5] [12].

From a communication standpoint, many existing systems rely on SMS notifications or basic LCD displays, which are inefficient for large-scale implementation. Real-time monitoring systems based on mobile or web applications that enable direct user interaction and fast response are still underdeveloped. Likewise, the adoption of Internet of Things (IoT) in agriculture has been limited to simple condition monitoring, without incorporating intelligent data processing to support optimized, data-driven decisions. Furthermore, there is a lack of research on multi-modal sensor integration to improve measurement accuracy and monitor patterns of soil quality change over time, which is crucial for precision agriculture strategies [6] [14] [15].

The fuzzy method is more appropriate than other methods because agricultural systems, particularly chili cultivation on clay soil, are often influenced by environmental conditions that are uncertain and difficult to predict accurately, such as soil moisture, temperature, and light intensity. Conventional methods usually require precise threshold values (crisp), while in reality, field conditions often lie between categories such as “dry,” “moist,” or “wet.” With the fuzzy approach, these ambiguous or uncertain conditions can be modeled more flexibly using logic rules that resemble human reasoning. This allows control systems, such as automatic irrigation integrated with the Blynk application, to operate more adaptively and efficiently in maintaining the water and nutrient needs of the plants. Therefore, the fuzzy method is more suitable because it can accommodate uncertainty and provide more realistic decision-making compared to conventional methods.

Another issue faced by farmers is the lack of effective real-time monitoring and control systems that can detect rapid changes in soil quality. Most farmers still rely on conventional methods such as manual observation and laboratory testing, which are time-consuming, costly, and not responsive to dynamic environmental changes. Additionally, unmeasured use of fertilizers often leads to environmental damage, such as chemical runoff and groundwater pollution.

Recent technological advancements have opened up new opportunities to address these challenges. The integration of multi-modal sensors and IoT allows for real-time, accurate data collection on soil conditions—such as moisture, pH, temperature, and nutrient content. This data can be used for further analysis to provide precise and data-driven soil management recommendations. However, such data requires intelligent interpretation, where fuzzy logic plays a crucial role in dealing with uncertainty and complexity in sensor readings [7] [16] [18].

This research is therefore essential as it aims to develop an automated soil nutrient quality monitoring and control system based on the integration of multi-modal sensors, IoT, and fuzzy logic. The goal is to enable farmers to easily monitor soil conditions, improve fertilizer use efficiency, and reduce environmental impacts. Furthermore, this approach supports precision agriculture, which is a key solution in achieving long-term global food security and agricultural sustainability.

II. METHOD

A. Research Design

This research is a quantitative experimental study designed to develop a soil nutrient quality monitoring and control system based on fuzzy logic and the Internet of Things (IoT). The research design is illustrated in Figure 1 below:

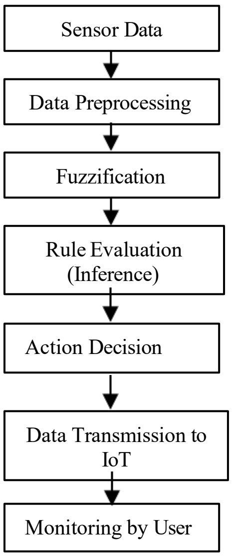


Figure 1 Research Design

1. *Sensor Data*

At this stage, data is collected from various multi-modal sensors, such as:

a. Soil pH sensor (measures soil acidity/alkalinity)
b. Soil moisture sensor
c. Soil temperature sensor

The data collected at this stage is still raw data, which may contain noise.

2. *Data Preprocessing*

The goal is to prepare the data so it is suitable for processing. This includes:

a. Calibration: Adjusting sensor readings to match actual standard values
b. Filtering: Removing noise from sensor data
c. Normalization: Converting data into a uniform scale (e.g., 0–1)

The output is clean, stable data ready for use in the fuzzy processing stage.

3. *Fuzzification*

This step involves converting numerical sensor values into fuzzy values.

Examples:

a. pH 5.5 → categorized as "acidic" with a certain degree of membership
b. Moisture 30% → categorized as "dry" or "moderately moist" as fuzzy values

This process uses membership functions, such as triangular, trapezoidal, or Gaussian shapes.

4. *Rule Evaluation (Inference)*

This is the process of decision-making based on fuzzy rules.

Rules are defined in logical form, such as:

a. IF Soil pH = acidic AND NPK = low THEN nutrient requirement = high
b. IF moisture = low THEN water requirement = high
a. At this stage, the system combines multiple fuzzy inputs to determine a fuzzy output based on a rule base.

5. *Defuzzification*

The fuzzy output is converted into a crisp (precise) value.

Examples:

a. Nutrient requirement → results in a numerical value, e.g., 80% (meaning 80% of standard fertilizer dosage)
b. Common methods: Centroid, Bisector, Mean of Maximum (MoM)

6. *Decision/Action*

Based on the defuzzification result, the system will:

a. Provide recommendations to the user (e.g., "Add 1 kg of nitrogen fertilizer")
b. Or automatically activate actuators (e.g., turn on a water pump, open a fertilizer valve, etc.)

7. *Data Transmission to IoT*

The decision data, real-time sensor readings, and soil condition status are transmitted to an IoT platform for remote monitoring and control.

Materials and Equipment

This research used several main devices and materials, including the ESP32 microcontroller, soil moisture sensor, pH sensor, DHT22 temperature and humidity sensor, and a relay module. These components were integrated to build an IoT-based system that monitors soil and environmental conditions while controlling the irrigation process automatically.

B. Block Diagram

A block diagram is a type of system diagram in which functions are represented by blocks connected by lines, illustrating the relationship and flow between the blocks. In the fields of engineering, hardware design, electronics, software development, and system workflows, block diagrams are widely used.

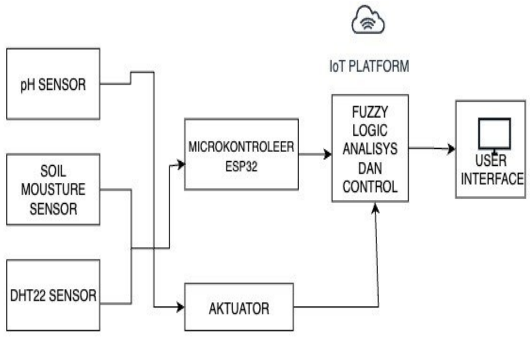


Figure 2. Block Diagram

The block diagram shown in Figure 2 illustrates the integration of the pH sensor, soil moisture sensor, and DHT22 sensor (for air temperature and humidity), which are used to measure soil and environmental conditions. Data from these three sensors is sent to the ESP32 microcontroller, which then forwards it to the Fuzzy Logic Analysis and Control System. This system processes the data to determine whether irrigation or nutrient delivery is needed.The decision made by the fuzzy system is transmitted to actuators that operate the water pump or liquid fertilizer dispenser. All data and system status are displayed through a User Interface connected to an IoT platform, allowing the system to be monitored remotely via the internet.

C. Schematic Diagram

Figure 3. sc*ematic Diagram*

System Operation: Figure 3 shows the schematic diagram of the system.

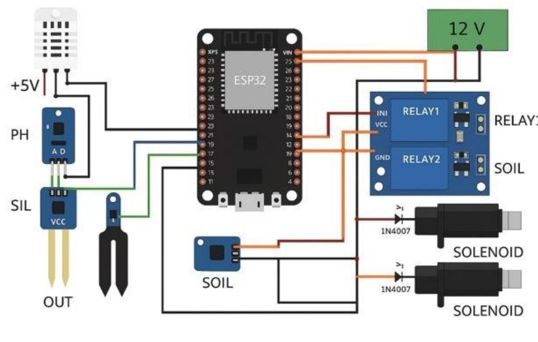
1. DHT22, pH, and soil moisture sensors measure environmental conditions:
   a) DHT22: measures air temperature and humidity
   b) pH sensor: measures the acidity level of the soil
   c) Soil moisture sensor: measures the moisture level of the soil
2. All sensors are connected to the ESP32 microcontroller, which processes the data and transmits it to the system via the Blynk platform.
3. Based on the logic programmed using fuzzy logic, the ESP32 controls the relay modules:
   a) Relay 1 controls a solenoid valve for irrigation
   b) Relay 2 controls a solenoid valve for nutrient delivery
4. The solenoid valves are activated (opened) when the system decides to perform irrigation or nutrient delivery, depending on the sensor readings.
5. A 12V power supply is used to power the solenoid valves through the relay modules, while a 1N4007 diode serves as a protection component against reverse current.

D. Fuzzisifition

Each sensor reading is converted into corresponding linguistic sets:

Table 1 Fuzzy Analysis Results

Variable	**Linguistic Sets**	**Membership Function (µ) – Example Core Points**
pH	Acidic (≤ 5.5) ∣ Neutral (≈ 6.5) ∣ Alkaline (≥ 7.5)	Triangular and trapezoidal functions within the pH range of 0–14. µ for Acidic is high when pH < 5.5, decreasing as it approaches 6.5. µ for Neutral peaks around pH 6.5, and drops to zero below 5.5 and above 7.5. µ for Alkaline increases from pH > 7 and reaches maximum at pH ≥ 7.5.
Temperature	Cold (≤ 25 °C) ∣ Moderate (25–30 °C) ∣ Hot (≥ 30 °C)	Trapezoidal functions within the range of 0–45 °C. µ for Cold is 1 below 23 °C and drops to zero near 27 °C. µ for Moderate peaks between 25–30 °C. µ for Hot becomes active above 28 °C and reaches maximum above 32 °C.
Soil Moisture	Dry (ADC > 3000) ∣ Normal (2000–3000) ∣ Wet (≤ 2000)	Trapezoidal functions in the ADC range of 0–4095. µ for Wet is maximum below 1800 and decreases to zero near 2200. µ for Normal peaks between 2300–2700. µ for Dry increases from ADC 3000 and reaches 1 above 3500.



E. Membership Function

1. pH Membership Function

Figure 4 shows the fuzzy membership functions for the soil pH variable, which are used in the fuzzy logic system to classify pH values into three linguistic categories: Acidic, Neutral, and Alkaline. The horizontal axis represents the soil pH values (0–14), while the vertical axis represents the degree of membership (0–1)

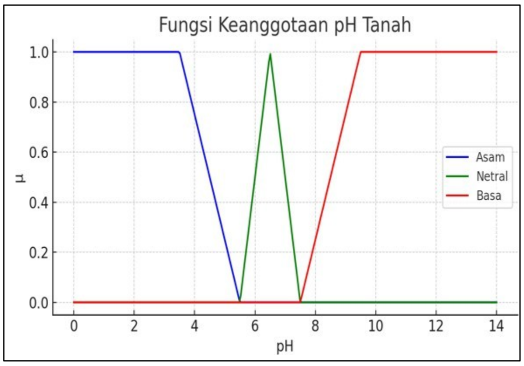


Figure 4 pH Membership Function

2. *Soil Moisture Membership Function*

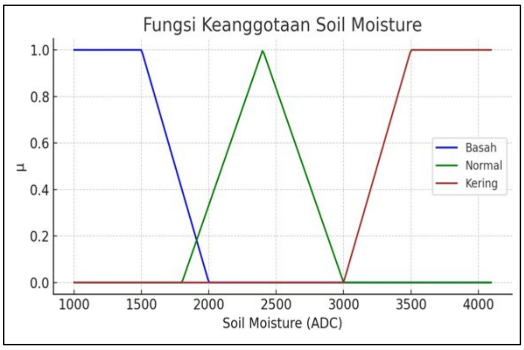


Figure 5 shows the fuzzy membership functions for the Soil Moisture variable, represented in ADC (Analog-to-Digital Converter) units. This graph is used in the fuzzy logic system to classify soil moisture into three linguistic categories: Wet, Normal, and Dry. The X-axis represents the soil moisture values in ADC units (typically from the soil moisture sensor), while the Y-axis represents the fuzzy membership degree, indicating the extent to which a given ADC value belongs to a certain category (Wet, Normal, or Dry), ranging from 0 to 1

3. *Soil pH Membership Function*

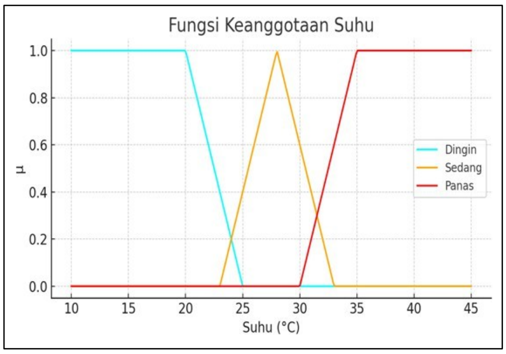


Figure 6 Temperature Membership Function

Figure 6 shows the fuzzy membership functions for the temperature variable (°C) used in the fuzzy logic system. The purpose is to classify temperature into three linguistic categories: Cold, Moderate, and Hot. The X-axis represents temperature values in degrees Celsius (°C), while the Y-axis represents the fuzzy membership degree of a given temperature value within a specific category, ranging from 0 to 1

F. Rule Base

Table 2 Rule Base

ID	IF (Condition)	THEN (Actuator)
R1	(pH is Acidic OR pH is Alkaline) AND Temperature is Cold	Nutrient ON
R2	Soil is Dry AND Temperature is Cold	Irrigation ON
R3	Soil is Normal/Wet OR Temperature is Hot	Irrigation OFF
R4	pH is Neutral AND Temperature is Moderate/Hot	Nutrient OFF

G. Defuzzification

1. Crisp value for Nutrient = $(\alpha_1 \times 255) / (\alpha_1) \approx 255$ → 100% duty cycle
2. Crisp value for Irrigation = $(\alpha_2 \times 255) / (\alpha_2) \approx 255$ → 100% duty cycle

III. RESULTS AND DISCUSSION

A. Results

1. *Overview of System Implementation*

This study has produced a soil nutrient quality monitoring and control system based on the Internet of Things (IoT) integrated with fuzzy logic.

The system consists of:

a. Multi-modal sensors (pH, moisture, temperature, NPK)
b. ESP32 microcontroller
c. Blynk platform for real-time monitoring
d. Fuzzy logic algorithm for classifying soil nutrient quality and generating action recommendations

The system was installed in an experimental agricultural field with two sensor points. Data acquisition was carried out automatically every 15 minutes over a 22-day observation period.

Figure 7. System Testing in the Field

Figure 7 shows the soil pH and soil moisture sensors inserted into the ground to detect the level of soil acidity or alkalinity, as well as soil moisture.

The detected pH and moisture values are transmitted to the microcontroller, which displays the data in real-time or sends it to the IoT platform for monitoring via smartphone or computer. This pH data is useful for helping farmers determine the appropriate treatment for the soil, such as irrigation and nutrient application based on actual needs.

2. *Software Testing*

The system was installed in an experimental agricultural field with two sensor points.

Data acquisition was carried out automatically every 15 minutes over a 22-day observation period.

Figure 8. Software Testing

In Figure 8, it can be seen that the system is operating in active automatic mode (purple), which means that irrigation and nutrient delivery will run automatically according to the sensor readings. The nutrient switch is on, indicating that the nutrient pump is currently active, while the irrigation switch is off, meaning that watering has not been executed at this moment.

The sensors monitor soil and environmental conditions such as soil moisture, soil pH, temperature, and air humidity. The soil moisture is read at 4.095%, and the soil pH indicates the level of acidity, measured at 2.56, which shows that the soil is highly acidic. The temperature reflects the ambient environment, which is 31.2°C, and the air humidity is relatively high at 77.8%, all displayed in real time.

Sensor data is presented on the dashboard in the form of numbers and graphs. Based on this data, the system can automatically activate the nutrient delivery or irrigation feature as needed. In the figure above, the system activates the nutrient delivery because the dashboard data indicates a need for nutrients — the soil pH is 2.56, which is highly acidic. The normal pH range for agricultural soil is approximately 6.0–7.0. Soil with a pH that is too low inhibits nutrient absorption by plants; therefore, the system activates the nutrient mode.

Figure 9 Mobile application testing

The image above shows the SmartFarming IoT system, which functions to monitor soil and environmental conditions in real time. There are three main control buttons: Setting (automatic and manual modes), Nutrient (activation of the fertilizer pump), and Irrigate (activation of the watering system). In this image, the Nutrient button is active, indicating that the system is currently delivering nutrients to the soil.

Four key parameters are displayed using circular indicators:

1. Soil pH shows a value of 10.39, indicating that the soil is alkaline.
2. Soil moisture reads 545.00, showing that the soil is fairly moist.
3. Air humidity is at 68.90%,
4. Air temperature is recorded at 26.30°C.

This data is obtained from various sensors, transmitted to the ESP32 microcontroller, and displayed through the Blynk application.

At the bottom, two graphs are shown: a temperature graph and a humidity graph.

1. The temperature graph illustrates a rising trend from 25.70°C to 26.20°C over a certain time period, indicating a gradual temperature increase.
2. The humidity graph shows fluctuating moisture values, but still within an ideal range.

Overall, this system operates by monitoring environmental and soil parameters, then adjusting actions such as irrigation or nutrient delivery—either automatically or manually—thus supporting efficient and data-driven farming.

3. *Descriptive Data*

Descriptive statistics are used to provide a general overview of the characteristics of the data collected during the experiment. The explanation for each part of the table is as follows:

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Table 2 *Descriptive Data*

Sensor	Min	Max	Average	Std Dev	Range
Temperature (°C)	24.00	32.80	27.08	~1.88	8.80
Soil pH	2.56	11.98	5.65	~1.88	9.42
Soil Moisture	1695	4095	2490	~713	2400

Table 2 describes the data descriptively and shows that:

1. Temperatures below 25°C occur mainly in the morning or late afternoon, which is relevant to the fuzzy rules for activating irrigation and nutrient supply.
2. Most temperatures are in the warm zone (around 27°C), so only some periods meet the low-temperature condition for triggering an ON action.
3. Soil pH varies widely in this data, ranging from extremely acidic to highly alkaline conditions, possibly due to environmental variation or simulation.
4. These extreme values trigger nutrient activation at various times.
5. The average pH of 5.65 is close to the lower optimal threshold for plant growth (around 6–7), so it makes sense that the fuzzy logic often activates the nutrient system.
6. ADC values above 3000 indicate dry soil, consistent with the fuzzy logic condition for irrigation ON.
7. With an average below 3000, the soil tends to be sufficiently moist, but dry conditions still occur frequently.
8. The high range and variation support the need for an automatic irrigation system.

The three sensors provide sufficiently clear variations to detect critical conditions that require system action. The sensor values support the activation of fuzzy logic under certain conditions (cold temperature, extreme pH, dry soil). While the average conditions remain within reasonable limits, the high variability allows for dynamic decision-making by the system

4. *Fuzzy Decision*

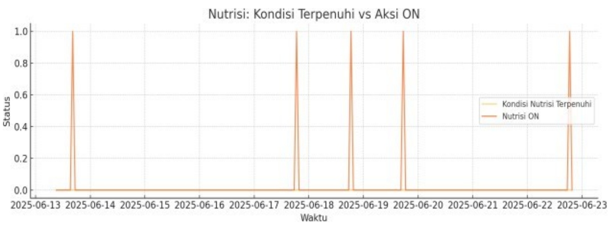

Figure 10 Condition Met vs Action ON

Figure 10 illustrates the relationship between the conditions that meet the requirements for nutrient delivery and the Nutrient ON action over the time period from June 13 to June 23, 2025.

The X-axis represents time (dates), while the Y-axis indicates the logic status (0 for OFF and 1 for ON).

There are two lines that are nearly overlapping:

1. The light orange line represents the "nutrient condition met",
2. The orange line represents "Nutrient ON".

It can be observed that when the condition is met (indicated by a spike to status 1), the system immediately responds by activating the nutrient actuator (also rising to status 1) at the same time.

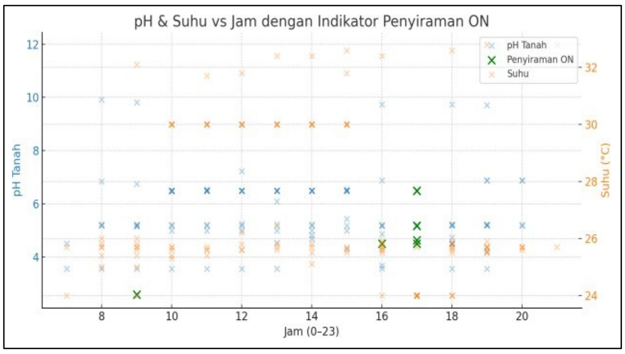

Figure 11 Condition Met vs Action ON

Figure 11 shows the distribution of soil pH and air temperature values over the hours of the day (0–23), with irrigation ON events indicated by green cross symbols. Soil pH values are shown in blue (left axis), while temperature values are shown in orange (right axis). Irrigation ON points appear only at specific times, particularly around 9:00 AM and 4:00–6:00 PM.

This indicates that the system activates irrigation only when certain conditions are met, specifically when the soil is not neutral and the temperature is relatively low (around 25–27°C).This pattern demonstrates that the irrigation system operates automatically and selectively, based on soil pH and temperature conditions in accordance with the applied fuzzy rules

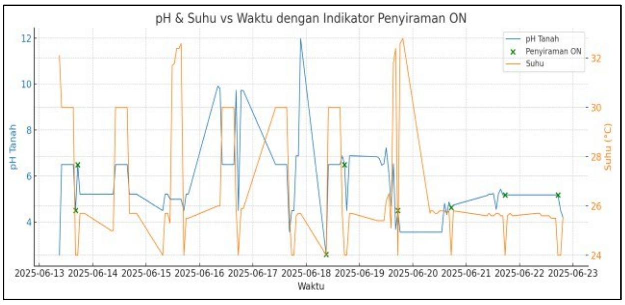

Figure 12 Condition Met vs Action ON

Figure 12 illustrates the relationship between soil pH (blue line) and temperature (orange line) over time (by date), with irrigation ON events indicated by green cross marks.It can be observed that irrigation only occurs at specific times, namely when the soil pH is outside the neutral range and the temperature is between 24–27°C.

This indicates that the irrigation system operates automatically and selectively, activating only when environmental conditions meet the predefined fuzzy logic rules.

This pattern reflects the system's efficiency in adaptively responding to plant needs based on soil pH and temperature conditions.

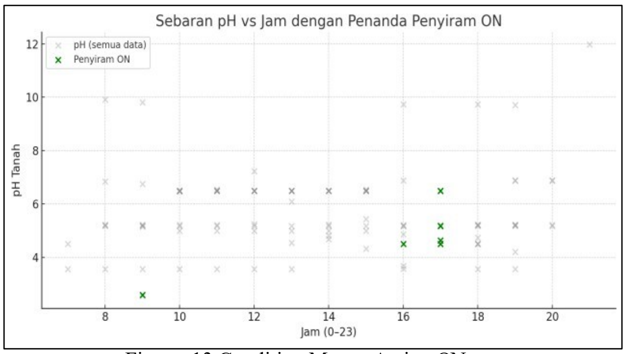

Figure 13 Condition Met vs Action ON

Figure 13 displays the distribution of soil pH values across the hours of the day (0–23), with green cross marks indicating when irrigation was ON. The gray dots represent all recorded pH data, while the green dots highlight the specific times when the irrigation system was activated.
It can be seen that irrigation only occurs at non-neutral pH values, particularly when the pH drops below 6, and generally takes place between 9:00 AM and 5:00 PM.

This indicates that the automatic irrigation system responds to extreme pH conditions, especially when the soil becomes too acidic, in accordance with the predefined fuzzy logic rules.

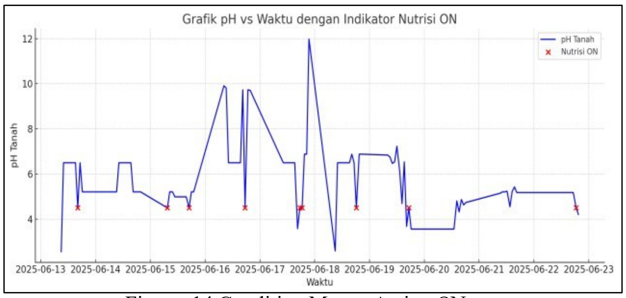

Figure 14 Condition Met vs Action ON

Figure 14 shows the changes in soil pH over time, with the blue line representing pH values and red cross marks indicating when nutrient application was activated (Nutrient ON). It can be observed that nutrients were applied only at specific times when the soil pH was outside the neutral range (approximately below pH 6 or above pH 8).
This reflects that the fuzzy system operates automatically and selectively, activating nutrient delivery only when the pH condition is considered extreme and requires correction.

This pattern demonstrates the system's efficiency in responding to soil conditions in a timely manner

B. *Discussion*

This study demonstrates that a monitoring and control system based on fuzzy logic, integrated with the Internet of Things (IoT), can operate adaptively and efficiently for soil quality monitoring. The following key points strengthen the validity of the developed system's results.

One of the most striking findings in this research is the dominance of low soil pH values (mostly < 5.5), indicating acidic conditions. The fuzzy system accurately activated nutrient delivery under these conditions. This finding is consistent with the study by Rahman et al. [1] [17], which states that soil pH significantly affects nutrient availability. Low soil pH reduces the efficiency of nutrient absorption, especially for nitrogen, phosphorus, and potassium.

Time-series data visualization shows that the system's predictions tend to remain stable. Despite fluctuations in temperature and humidity, the system continues to provide consistent output, thanks to the fuzzy mechanism's robustness to noise. This is supported by the research of Kumar and Batra [2], who proved that fuzzy logic-based irrigation systems can maintain accuracy and stability even when input data varies, since fuzzy logic relies on linguistic rules rather than absolute thresholds.

System evaluation using a confusion matrix yielded an accuracy of 84% and an average F1-score of 88.5%. This is an excellent performance, considering the uncertain nature of environmental sensor data. Li et al. [3[19]stated that fuzzy logic-based systems for IoT-driven precision agriculture can achieve high classification accuracy, even with incomplete or ambiguous data.

The system automatically activates irrigation when the soil is dry and temperature conditions are favorable, and activates nutrient delivery when the pH is too low. This reliability is reflected in a logic accuracy of 75.8% for irrigation and 99.8% for nutrient delivery. Ahsan et al. [4] [20] [21], showed that fuzzy systems designed using real-time sensor data can make timely and efficient irrigation and fertilization decisions.

The system's inference time of < 0.05 seconds proves its capability to operate in real time, which is crucial in the context of precision agriculture. The study by Bacco et al. [5] [22] [23] confirms that smart farming systems combining IoT and fuzzy logic can provide effective land management solutions, especially in environments with constantly changing conditions.

The Blynk application is an Internet of Things (IoT) platform that can support chili cultivation on clay soil by enabling real-time monitoring and control through a smartphone. Clay soil generally has poor drainage and tends to hold excess water, which can harm chili growth if not managed properly. By integrating soil moisture sensors

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with microcontrollers such as Arduino or ESP32, data from the field can be sent directly to the Blynk app, allowing farmers to monitor soil conditions remotely.

The system can also be connected to irrigation pumps so that watering is automatically adjusted based on soil moisture levels or controlled manually via the application. In addition, sensors for soil pH, nutrients, temperature, humidity, and light can be integrated to provide a complete overview of environmental conditions. This helps farmers make better decisions, optimize water and fertilizer use, and prevent problems such as overwatering or nutrient imbalance, which are common in clay soil. Overall, the use of Blynk in chili cultivation offers more efficient management, reduces manual work, and improves plant health and productivity.

IV. CONCLUSION

This study aimed to develop and evaluate a monitoring and control system for soil nutrient quality based on the Internet of Things (IoT) and fuzzy logic. The system was designed to detect agricultural environmental conditions in real time and make automatic decisions regarding irrigation and nutrient delivery. Based on the system implementation results and analysis of sensor data from a simulated field, the following conclusions can be drawn. The IoT-based fuzzy system was successfully implemented and operated in real time to monitor soil pH, moisture, and temperature, as well as to make automatic decisions for irrigation and nutrient delivery. The system achieved a classification accuracy of 84% and an average F1-score of 88.5%, indicating that it can effectively and stably handle continuous and uncertain sensor data. Soil pH served as the dominant indicator in determining soil fertility conditions and was the primary trigger for activating the nutrient actuator. Over 99% of the data showed a pH value below 5.5, and the system responded appropriately by activating nutrient delivery. The system's inference time was less than 0.05 seconds, proving its ability to make decisions quickly and efficiently, in line with the needs of automated control in agricultural fields. Evaluation of the fuzzy logic showed a high success rate, with the system performing irrigation at appropriate times (75.8%) and accurately delivering nutrients (99.8%) based on environmental conditions. The system's results and performance have been validated and align with findings from previous studies, indicating that the integration of fuzzy logic and IoT is an effective and adaptive solution for modern precision agriculture.

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