IoT-Enabled Smart Farming System Based on Sugeno Fuzzy Logic for Land Monitoring, Automated Irrigation, and Fertilization Recommendation

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Abstract- ***Conventional farming systems are widely practiced without considering field conditions, including temperature, soil moisture, and soil pH, leading to inaccurate irrigation, fertilization, and crop selection. This study designed and implemented an Artificial Intelligence and Internet of Things-based smart farming system using the Sugeno Fuzzy Logic method to support real-time land monitoring, fertilizer recommendations, and automatic watering control. An experimental method was applied through literature review, hardware and software design, multisensor integration, implementation, testing, and evaluation. The system integrates an ESP32 controller, a DHT11 sensor, a soil moisture sensor, a soil pH sensor, an ultrasonic water-level sensor, an ACS758 current sensor, an Android-based Blynk application, and solar panels as the energy source. The results show that the system displayed temperature, humidity, soil pH, reservoir water status, fertilization status, and watering status in real time via the Android app. Sensor testing showed reliable performance, with the DHT11 producing average differences of 0.675°C for temperature and 1.75% for humidity compared with BMKG reference data. The soil moisture sensor identified dry, normal, and wet soil conditions with average values of 23.73%, 47.50%, and 80.23%, respectively. The pH sensor recorded average values between 6.48 and 6.72, while the ultrasonic sensor achieved an average reservoir-level error of 0.62%. Solar panel testing produced average voltages of 13.89 V on the multimeter and 13.61 V on the solar charge controller. Fuzzy logic testing confirmed that the system could generate fertilizer recommendations and regulate irrigation valve ON/OFF status based on temperature, humidity, and soil pH. Therefore, the developed system supports efficient, adaptive, and data-driven agricultural management.***

Keywords — Artificial Intelligence, IoT, Fuzzy Logic Sugeno, smart farming, fertilization, automatic watering

I. Introduction

Many factors influence agricultural productivity, such as natural conditions, human input, technology, and policies. Natural factors such as temperature, rainfall, sunlight, and wind are closely tied to climate and weather, which play major roles in plant growth. Climate change brings more extreme weather and changes in rainfall, making it harder to maintain productivity. Traditional farming methods are less effective at handling these new challenges. To adapt, farmers need flexible strategies that use real-time data, but modern machine learning methods have not yet been widely used for this purpose [1] . Climate change causes stress in ornamental plant farming by altering temperature, light, and water conditions, all of which affect plant growth. Using machine learning and Internet of Things (IoT) sensors to monitor soil moisture [2] helps conserve water, maintain optimal humidity, and support healthy plant growth. Agriculture today faces two main problems: a growing population and the effects of climate change. These issues lead to increased plant diseases and pests, often due to water shortages and poor fertilization [3]. Using computer vision and IoT for monitoring and early disease detection enables faster, more effective disease management [4]. Traditional farming also struggles with uneven resource use, low efficiency, and environmental problems [5]. Artificial intelligence helps make agricultural land planning more accurate, improves crop yields, and supports sustainable farming [6]. Today, farmers use drones to monitor crops and smart irrigation systems [7] with sensors to use water and fertilizer more efficiently. This not only boosts crop yields [8] but also reduces waste and helps the environment by using resources wisely [9]. Still, many of these systems are not yet connected to the Internet of Things (IoT) [10]. In traditional greenhouse farming, there are ongoing ethical, social, and technical challenges worldwide. Greenhouses offer a controlled environment, using Arduino-based control systems, IoT, and machine learning to manage plants, enabling remote management [11]. Soil fertility, which includes nutrients like nitrogen, phosphorus, potassium, other elements, organic matter, and soil structure, plays a key role in plant growth. Human factors, such as having enough labor for planting and fertilizing, are also important for healthy crops. Because of these factors, there is a need for agricultural monitoring systems that use artificial intelligence and cloud computing to manage pesticides, fertilizers, water, soil, and air quality [12] with artificial neural network (ANN) models [13]. Use the Internet of Things (IoT), wireless sensor networks (WSN), and network-layer architecture, leveraging the AI-IoT model [14], [15]. This system allows for real-time monitoring and supports precision agriculture. Recent progress in AI for agriculture includes using soil and weather sensors, IoT, drone imagery, and machine learning (ML) to predict water needs. Still, there are challenges, such as improving sensor reliability, collecting long-term data, and combining edge and cloud computing [16], [17]. Plant diseases can significantly reduce crop yields and threaten global food security [18]. Technologies such as machine vision and artificial intelligence, including deep learning, neural networks, and image processing, help quickly and accurately detect plant stress without damaging the plants [19], [20]. The rise of the Internet of Things (IoT) and cloud-based platforms for managing farm equipment, along with layered IoT systems, allows farms to optimize their operations more effectively. IoT also makes it easier for Farm Management Information Systems (FMIS) to connect, helps farms adjust productivity in real time, and simplifies crop data [21], [22]. Today, smart irrigation systems help address water shortages, especially in dry regions. However, their high cost underscores the need for affordable IoT sensors for small farms[23]. Smart irrigation is most effective when it uses real-time data from sensors, together with communication systems and other smart devices [24]. So far, these smart irrigation systems have only been tested on a small scale and are still limited in use [25]. A major challenge in modern agriculture is managing the large amounts of data generated, this data comes from environmental and soil sensors, as well as network devices, and is processed using cloud computing and data analytics frameworks [26].

Farmer skills play a big role in productivity. Still, many farmers rely on traditional planting, watering, and fertilizing practices that may not align with their land's needs, leading to lower yields. Many farming problems are linked to soil conditions, especially moisture, temperature, and pH, all of which are important for plant growth. Although traditional methods are still widely used, there is now a need for smart farming systems that leverage technologies such as artificial intelligence and the Internet of Things (IoT). These digital tools help design and develop smart farming systems that let farmers monitor their fields in real time, decide when to water and fertilize, and boost yields while saving costs.

This project helps farmers track humidity, temperature, and soil pH, enabling them to select the best crops for their land. The system checks these conditions in real time and can automatically control drip irrigation. Farmers can also get information about fertilization needs through an Android app that uses IoT. The smart farming system brings together artificial intelligence and IoT to monitor land, control water pumps, manage drip irrigation, and schedule fertilization. This makes it easier for farmers to manage their crops and get better harvests. The Smart Farming System was created, tested, and used with the Women's Farmers Group in Manggar Village, South Balikpapan District, Balikpapan City.

Recent research has made progress in using sensors, IoT, machine learning, and artificial intelligence in agriculture. Still, many studies address only one specific function, such as watering, disease classification, environmental monitoring, crop recommendations, or greenhouse management. In addition, some research is only conceptual, based on simulations or lab tests, so there is still limited integrated use in real farming conditions. This research introduces a new way to develop an integrated smart farming system using IoT and fuzzy logic. The system monitors temperature, soil moisture, pH, water levels, voltage, and current, and automatically controls drip irrigation and reservoir filling. It also shows fertilizer application status and displays all conditions in real time through an Android app.

It uses artificial intelligence, DHT11 temperature and humidity sensors, soil moisture and pH sensors, ultrasonic and current voltage sensors, ESP32 microcontrollers, wireless networks, Blynk IoT on Android devices, and solar panels.

II. Research Method

This study used an experimental approach to design, build, and test a smart farming system that uses Artificial Intelligence and the Internet of Things. The research process included several stages: literature review, system architecture design, electronic circuit design, setting fuzzy-logic parameters, integrating hardware and software, field implementation, sensor testing, fuzzy-logic testing, IoT connection testing, and analyzing system performance. The literature review helped identify key agronomic factors for plant growth, especially temperature, soil moisture, and soil pH. The hardware setup combined the DHT11 sensor, soil moisture sensor, soil pH sensor, JSN-SR04T ultrasonic sensor, ACS758LCB-050B current sensor, relay, pump, watering valve, ESP32, solar panel 12 V 100 Wp, solar charge controller 12 V PWM/MPPT solar charge controller, battery, inverter, and the Blynk app.

The system architecture consists of four main layers: the input layer, the processing layer, the output layer, and the energy layer. The input layer receives data from the agricultural environment. The DHT11 sensor is used to read air temperature and humidity; the soil moisture sensor is used to determine the water content in the growing medium; the soil pH sensor is used to determine the soil acidity level; the ultrasonic sensor is used to read the water level in the reservoir; and the ACS758 sensor is used to monitor the pump current.

The processing layer uses the ESP32 as the main controller. The ESP32 DevKit V1 receives sensor data, performs analog and digital readings, runs the Sugeno fuzzy logic algorithm, controls relays, and sends data to the Blynk application via Wi-Fi. The output layer consists of an Android application, a pump relay, a watering valve relay, and a system status display. The Android application displays temperature, soil moisture, soil pH, reservoir water status, fertilization status, and watering status in real time. The energy layer uses solar panels as the main energy source, a solar charge controller as a battery charger, a battery for energy storage, an inverter for AC loads, and an adapter or buck converter to supply DC power to the ESP32 and sensors.

III. Results and Discussion

3.1 Internet of Things-Based Smart Farming Design

Building a smart farming system with the Internet of Things (IoT) requires both hardware and software design. The process includes making an input/output (I/O) module to control water pumps, manage watering or drip irrigation, and schedule automatic fertilization with artificial intelligence. This system provides real-time land monitoring, automated water and irrigation control, and timely fertilization updates. Figure 1 shows the design of the smart farming system, which uses intelligent methods and works with Android devices.

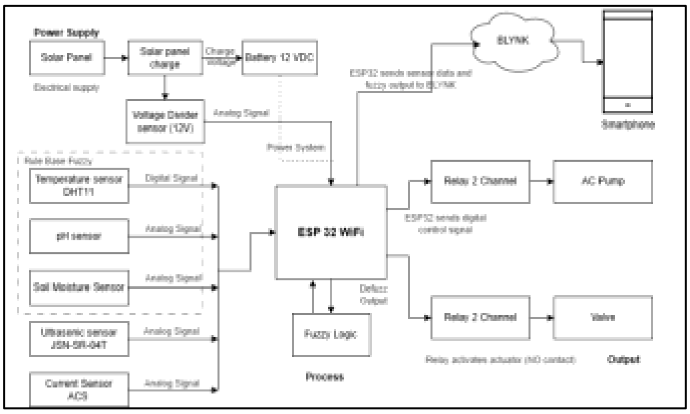


Figure 1. Smart Farming System Block Diagram

The block diagram shows that smart agricultural technology comprises several main components: input, processing, output, and resource. (1) The DHT11 sensor detects the temperature of the agricultural land environment. (2) The pH sensor detects the acidity and alkalinity of the agricultural soil. (3) Soil moisture sensor. This sensor measures soil moisture, which serves as input data for agricultural soil moisture. (4) The ultrasonic sensor detects the water volume in the storage tank. (5) The ACS 758 sensor monitors the pump current and the power consumption of the solar panels. (6) The ESP32 WiFi sensor processes data from each sensor. In the workflow, the ESP32 acts as a controller, issuing commands to monitor the condition of the agricultural land and the volume of the water reservoir, activating the pump, regulating the water flow rate during drip irrigation, providing fertilizer information, and sending notifications to Blynk for display on Android. The block diagram illustrates a smart technology system that integrates solar panels and a sensor security system. This system consists of several key components categorized into input, processing, output, and resource components. Fuzzy logic is an intelligent method that underlies the ESP32 programming architecture. Fuzzy algorithms are used to determine fertilization times and regulate watering based on soil conditions. (7) AC pump and valve: The pump generates pressure to move water from the source or storage tank to the irrigation hose and drip points. The pump operates according to commands from the ESP32 after the sensor data is processed using fuzzy logic. When soil moisture falls below a specified level, the system sends a signal to activate the pump. (8) Solar panels act as a power source, converting solar thermal energy into electricity. A charge controller regulates the current and voltage from the solar panels to charge the batteries. The batteries store electrical energy to supply power to the system. The adapter converts AC voltage to DC to power the ESP32 and sensors. (9) Blynk interface: provides information on fertilized and unfertilized plants, opens and closes watering valves via the app, turns the pump on/off via the app, and monitors the voltage and current from the solar panels. (10) Database or cloud: functions to store all data collected from sensors and actuators, store historical records such as soil moisture, temperature, soil pH, water level, pump operation, and energy consumption, and the data remains stored and can be accessed even if the local microcontroller loses power.

The figure shows how sensing, intelligent decision-making, control, communication, and renewable energy work together in a single system. The ESP32 processes sensor data using fuzzy logic and then executes actions such as irrigation, fertilization, reservoir filling, and monitoring.

3.2 System Flowchart Design

A flowchart illustrates how the system functions, with each interconnected part generating work output from the data processing procedure. A flowchart of the tool's overall performance is displayed in Figure 2.

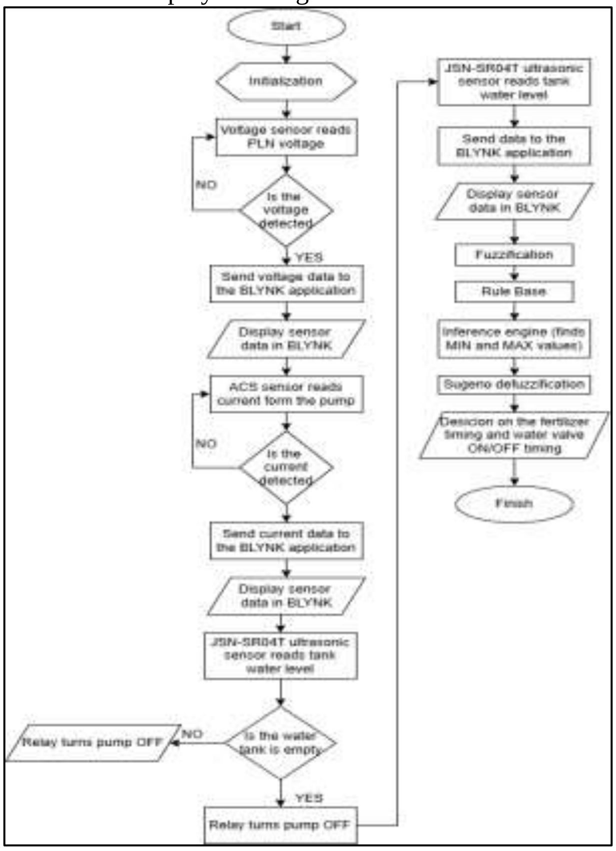
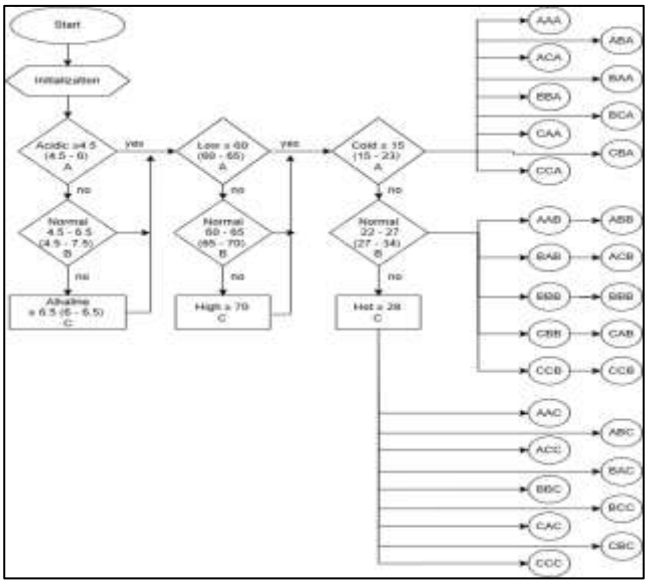


Figure 2. Smart Farming Flowchart

The following describes the device's operating system's general flowchart: (1) *Sensor Initialization and Startup*, The system is activated, all sensors are activated and prepared.
(2) Monitoring Voltage, The DC voltage-divider sensor measures the system voltage. If the voltage is read, the data is sent to the Blynk application via ESP32 (WiFi). The data is displayed in Blynk, if it is not read, the sensor rereads the voltage. *(3).Monitoring AC Current* , The ACS sensor reads the AC current. If the current is read, data is sent to Blynk via the ESP. Displayed in Blynk. If not, the system rereads the current. (4)*Water Detection in Reservoirs*, The JSN-SR04T Proximity Sensor detects whether the reservoir is empty or full. If empty, the relay activates and activates the pump. When the reservoir reaches a certain level, the relay and pump are turned off. *(5) Farm Monitoring*, Agricultural land monitoring involves installing sensors, including a DHT11 sensor to measure temperature and humidity, a soil moisture sensor to measure soil moisture, and a pH sensor to measure soil acidity. Data from the sensors is sent to Blynk for display on Android. *(6) Fuzzy Logic Processing*, Fuzzification data converted into fuzzy values (e.g., temperature "hot", soil "dry"), building fuzzy rules (rule base), fuzzy IF-THEN. The inference engine continues the process using the MIN-MAX implication function. *(7) Sugeno Defuzzification*, The output from the fuzzy process is converted back to exact values (numbers) using defuzzification. The results are used to determine when to fertilize and when to turn the irrigation valve on or off. *(8) Finished*, The system uses sensor data and fuzzy logic to automatically monitor and control processes. It works in real time. The flowchart shows that the system works in a closed loop. It monitors environmental and electrical conditions and adjusts automatically. As a result, there is less need for people to control it by hand. Figure 3 shows the flowchart for the intelligent, logic-based fertilizer information system. It outlines how the IoT-based automatic monitoring and fertilization system works using fuzzy logic.



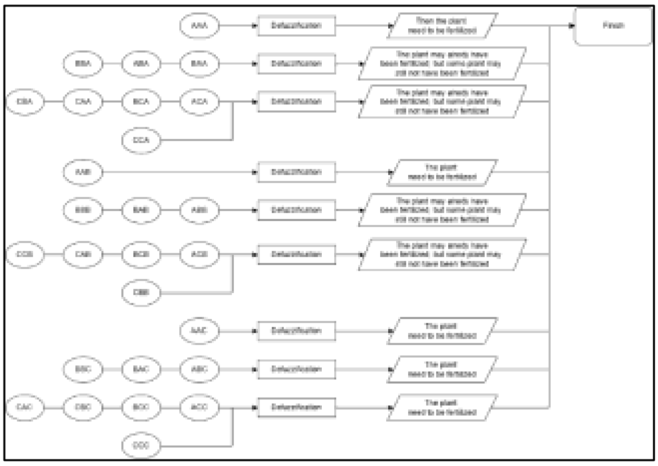
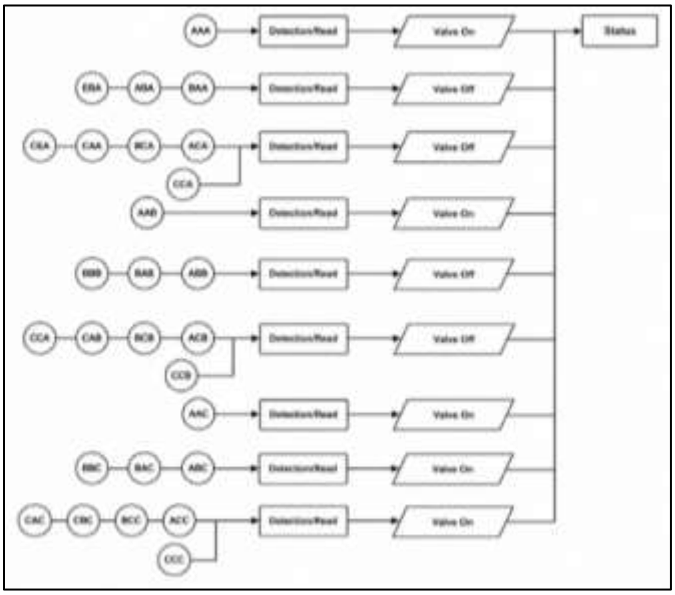


Figure 3. Smart Fertilization Information System

Figure 3 illustrates the workflow of the smart fertilization information system using Sugeno fuzzy logic. The system starts with sensor initialization and data acquisition from three main input variables: soil pH, soil humidity, and temperature. These inputs are converted into linguistic categories through the fuzzification process, such as acid, normal, or alkaline for pH; low, normal, or high for humidity; and cold, normal, or warm for temperature. The fuzzified values are then evaluated using a fuzzy rule base to determine the plant's fertilizer status. Using the Sugeno defuzzification method, the system produces a crisp output indicating whether the plant is fertilized. The final result is displayed through the IoT-based Android interface, allowing farmers to monitor fertilizer requirements in real time. This mechanism helps improve fertilization accuracy, reduce unnecessary fertilizer use, and support better soil fertility management. Figure 4 presents a flowchart that illustrates how the automatic drip irrigation system uses fuzzy logic for smart control.



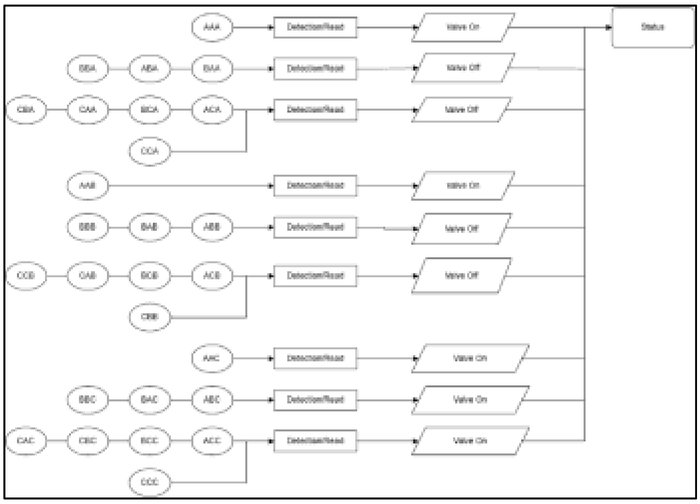
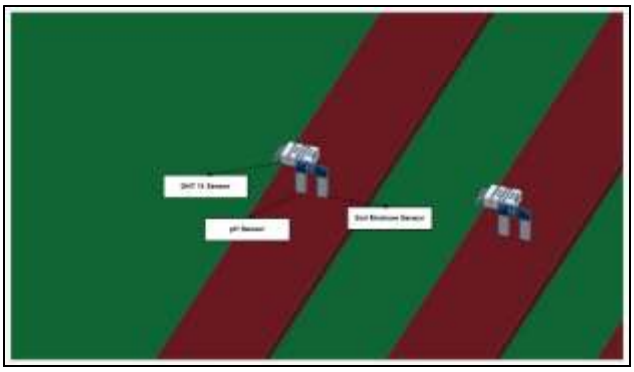


Figure 4. Smart Watering Information System

Figure 4 shows the workflow of the smart watering information system for automatic drip irrigation control. The system processes soil pH, soil humidity, and temperature data obtained from sensors installed in the agricultural area. These numerical sensor readings are converted into fuzzy linguistic values and evaluated using the fuzzy rule base. Soil humidity becomes the dominant input in determining irrigation needs, while temperature and pH strengthen the decision-making process. When soil humidity is low, especially under warm conditions, the system generates an ON output, opening the valve and allowing water to flow to the plant area. When the soil humidity is normal or high, the system generates an OFF output to prevent excessive watering. The final valve status is obtained through Sugeno defuzzification and can be monitored through the Android-based IoT interface. This system enables more efficient irrigation control based on real-time field conditions.

3.3 Tool Design

The tool shown in Figure 5 is designed to monitor the temperature, humidity, and pH of agricultural soil. It can also control the pump that refills water tanks and has an information system to track plant fertilization.



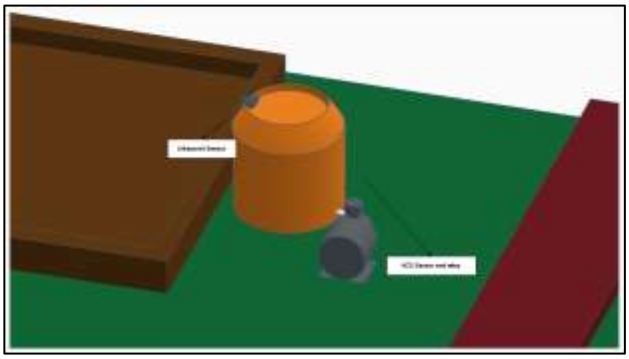


Figure 5. Tool Design, Sensor Placement, Reservoir and Pump

The figure shows that we built and tested the proposed architecture as a working prototype. It is important to place the sensors correctly because poor placement can make temperature, moisture, pH, and water-level readings less reliable.

4 Fuzzy Logic Design

This study focuses on designing a tool that applies fuzzy logic to artificial intelligence in agricultural technology, using an intelligent system built on the Internet of Things (IoT). We use the Fuzzy Sugeno method. The fuzzy logic design includes membership functions (fuzzification), rule bases, and defuzzification, as described below:

Fuzzification

Set up the membership functions according to how your device operates and its configuration settings.

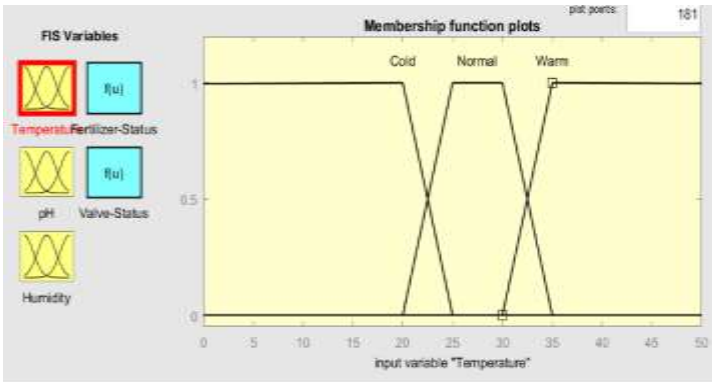


Figure 6. Temperature Membership Function

The temperature variable was divided into three linguistic categories: cold, normal, and warm. The membership function range was set from 0°C to 50°C to cover possible environmental temperature variations in agricultural land. The cold category was defined as temperatures below approximately 25°C, the normal category was centered around 25–30°C, and the warm category was defined as temperatures above 30°C. The normal temperature range was selected because many crop physiological processes, including photosynthesis and growth, generally perform well around 20–30°C, while temperatures above 30°C may increase evapotranspiration and plant water demand.

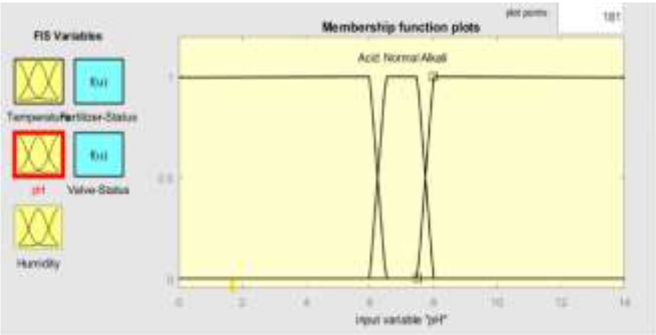


Figure 7. pH Membership Function

The soil pH variable was divided into three linguistic categories: acid, normal, and alkaline. The pH range was set from 0 to 14, following the general pH measurement scale. The normal pH range was centered on 6.0–7.5 because this interval is generally suitable for most plants, as many essential nutrients become more available within it. Soil with a pH below this range tends to be acidic, while soil above it tends to be alkaline. Both acidic and alkaline soil conditions may reduce nutrient availability and decrease fertilizer effectiveness.

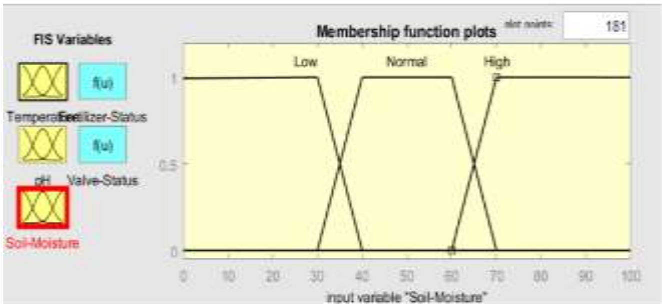


Figure 8. Soil Mouisture Membership Function

The soil moisture variable was divided into three categories: low, normal, and high. The membership function range was set from 0% to 100% because the soil moisture sensor output was expressed as a percentage. The threshold values were determined from sensor calibration under dry, normal, and wet soil conditions. In the sensor test, dry soil produced an average value of 23.73%, normal soil produced 47.50%, and wet soil produced 80.23%. Therefore, the fuzzy boundaries were arranged to separate these three soil conditions while maintaining transition areas between categories.

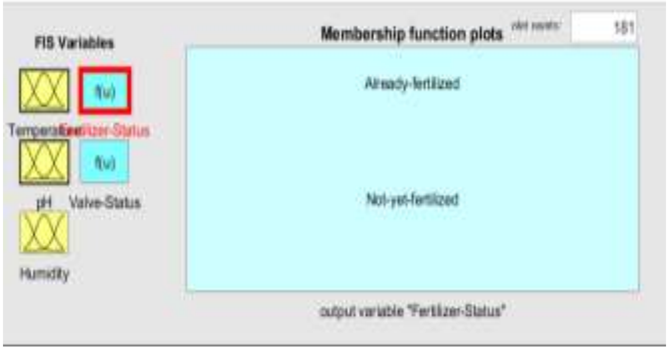


Figure 9. Fertilizer Status Membership Function

The use of constant output values is appropriate for the Sugeno method because the final decision is calculated via weighted-average defuzzification. A decision threshold can be applied to convert the crisp output into a practical recommendation. For binary classification, a threshold of 0.5 may be used, where output values below 0.5 indicate “no fertilizer required” and values equal to or above 0.5 indicate “fertilizer required.” However, the final threshold should be adjusted consistently with the rule base and field validation results

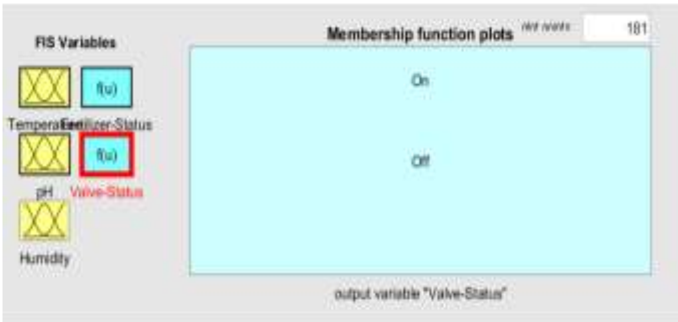


Figure 10. Valve Status Membership Function

The valve decision is mainly determined by soil moisture because this variable directly indicates water availability in the planting medium. Low soil moisture triggers an ON output, while normal or high soil moisture triggers an OFF output. Temperature is used as a supporting variable because warmer conditions can increase evaporation and plant water demand. Soil pH is included as an additional input to maintain consistency with the overall fuzzy decision system. A decision threshold of 0.5 can be used, where output values below 0.5 indicate valve OFF and output values equal to or above 0.5 indicate valve ON.

Rule Base

At this point, the input and output memberships, which use linguistic variables, are organized into rule bases. These rule bases help control the output of the fertilization and irrigation system using fuzzification. Table 1, presents the fuzzy control rule base.

Tabel 1. Data Parameter

Rule	Temperature	pH	Soil Moisture	Fertilizer Status	Valve Status
R1	Cold	Acid	Low	Not Fertilized	On
R2	Cold	Acid	Normal	Fertilized	Off
R3	Cold	Acid	High	Fertilized	Off
R4	Cold	Normal	Low	Not Fertilized	On
R5	Cold	Normal	Normal	Not Fertilized	Off
R6	Cold	Normal	High	Not Fertilized	Off
R7	Cold	Alkali	Low	Not Fertilized	On
R8	Cold	Alkali	Normal	Fertilized	Off
R9	Cold	Alkali	High	Fertilized	Off
R10	Normal	Acid	Low	Not Fertilized	On
R11	Normal	Acid	Normal	Fertilized	Off
R12	Normal	Acid	High	Fertilized	Off
R13	Normal	Normal	Low	Not Fertilized	On
R14	Normal	Normal	Normal	Fertilized	Off
R15	Normal	Normal	High	Not Fertilized	Off
R16	Normal	Alkali	Low	Fertilized	On
R17	Normal	Alkali	Normal	Fertilized	Off
R18	Normal	Alkali	High	Fertilized	Off
R19	Warm	Acid	Low	Not Fertilized	On
R20	Warm	Acid	Normal	Fertilized	Off
R21	Warm	Acid	High	Fertilized	Off
R22	Warm	Normal	Low	Not Fertilized	On
R23	Warm	Normal	Normal	Fertilized	Off
R24	Warm	Normal	High	Not Fertilized	Off
R25	Warm	Alkali	Low	Not Fertilized	On
R26	Warm	Alkali	Normal	Fertilized	Off
R27	Warm	Alkali	High	Fertilized	Off

Table 1 shows 27 fuzzy rules based on different combinations of temperature, soil pH, and soil moisture. Each variable has three linguistic categories, resulting in (3*3*3=27) combinations. Therefore, the rule base has 100% coverage of all possible input combinations. The rules highlight that soil moisture is the main factor for controlling the irrigation valve. When soil moisture is low, the valve usually turns on, and when it is high, the valve turns off. Fertilizer is mainly recommended when the soil pH is normal. These rules help the system turn environmental data into decisions about irrigation and fertilization. The valve rule base is acceptable because it is consistent with soil moisture conditions. However, the fertilization rule base needs revision or clearer justification because some rules are not fully aligned with agronomic reasoning.

Defuzzification

Defuzzification is the step that determines the results of the rules in the rule bases. The method used is the weighted average method for Sugeno Fuzzy Logic.

3.5 System Test Results

Testing was conducted over five consecutive days at three test sites. Data was collected four times daily: at 7:00 AM, 11:00 AM, 2:00 PM, and 4:00 PM. Each sensor was tested at the same time and location to ensure consistent comparison of temperature, soil moisture, pH, and watering status.

DHT11 Sensor Testing

The DHT11 temperature and humidity sensor was tested, and the results are shown in Table 2.

Tabel 2. DHT11 sensor testing

Time	DHT11 Temperature (°C)	BMKG temperature (°C)	Temperature Difference	DHT11 Humidity (%)	BMKG Humidity (%)	Humidity Difference
07:00	25.4	26.0	0.6	89.0	85.0	4.0
11:00	30.1	31.0	0.9	71.0	70.0	1.0
14:00	32.5	33.0	0.5	64.0	63.0	1.0
16:00	31.3	32.0	0.7	66.0	65.0	1.0
Mean	29.83	30.5	0.675	72.5	70.75	1.75

We collected data four times a day at 7:00 AM, 11:00 AM, 2:00 PM, and 4:00 PM. Each sensor was tested at the same location and time to ensure consistent comparisons of temperature, soil moisture, soil pH, and watering status. All sensors were tested at the same location and time. This approach enabled consistent comparison of temperature, soil moisture, soil pH, and watering status data. The DHT11 sensor measured an average temperature of 29.83 °C, while the BMKG reference data showed 30.50 °C, giving an average difference of 0.675 °C. For relative humidity, the sensor averaged 72.50%, compared to 70.75% from BMKG, with a difference of 1.75%. These results show that the DHT11 sensor tracks daily environmental changes well and is reliable enough for real-time smart farming monitoring.

Sensor validation results using Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{1}$$

$$MAE = \frac{1}{4} \sum_{i=1}^{n} |25.4 - 26| + |30.1 - 31| + |32.5 - 33| + |31.3 - 32|$$

$$\mathrm{MAE} = 0.675$$

The DHT11 temperature MAE of 0.675°C is below the permissible limit of 1°C. The humidity MAE of 1.75%RH is also below the permissible limit of 5%RH. In addition, meaning that both measurements can be categorized as accurate enough for real-time agricultural monitoring.

Soil Moisture Sensor Testing

We tested the soil moisture sensor by placing it in soil with different conditions. The results are listed in Table 3.

Tabel 3. Soil moisture sensor testing

No	Soil Conditions	Sensor 1 (%)	Sensor 2 (%)	Sensor 3 (%)	Mean (%)
1	Dry	23.4	25.1	22.7	23.73
2	Normal	48.3	46.7	47.5	47.5
3	Wet	79.0	81.2	80.5	80.23
	Mean	50.23	51.0	50.23	50.49

The soil moisture sensors identified dry, normal, and wet soil, with average readings of 23.73%, 47.50%, and 80.23%. The small differences between the three sensors suggest their measurements are consistent. Soil moisture sensor performance, by determining the standard deviation and coefficient of variation using the formula :

$$SD = \sqrt{\sum_{i=1}^{n} \frac{(xi - \hat{x})^2}{n-1}} \tag{2}$$

$$CV = \frac{SD}{\hat{x}} x\ 100\% \quad (3)$$

From the calculations using the formula, the standard deviation is 1.23 and the coefficient of variation is 5.20% for dry soil conditions.

Tabel 4. CV soil moisture sensor

Soil Condition	Mean	Standard Deviation	Coefficient of Variation (%)	Permissible Limit	Status
Dry	23.73%	1.23	5.20%	CV ≤ 10%	Accepted
Normal	47.50%	0.80	1.68%	CV ≤ 10%	Accepted
Wet	80.23%	1.12	1.40%	CV ≤ 10%	Accepted

The CV values for all soil conditions were below 10%. This indicates that the three soil moisture sensors produced consistent readings. The largest CV was observed in dry soil at 5.20%, but this value remains within the acceptable repeatability limit.

pH Sensor Testing

The pH sensor was tested under various soil conditions, with the results shown in Table 5.

Tabel 5. pH sensor testing

Day	Garden 1 (pH)	Garden 2 (pH)	Garden 3 (pH)	Mean (pH)
1	6.5	6.8	6.7	6.67
2	6.4	6.7	6.6	6.57
3	6.5	6.6	6.7	6.60
4	6.6	6.9	6.8	6.77
5	6.4	6.6	6.5	6.50
Mean	6.48	6.72	6.66	

Soil pH readings from the three garden sites ranged from 6.4 to 6.9, with average values of 6.48, 6.72, and 6.66. This small range shows that the sensors gave consistent results over the five-day period. Overall, the soil was slightly acidic to nearly neutral, which makes it suitable for use in the fuzzy fertilization recommendation system.

Using formulas (2) and (3), the performance of the pH sensor, based on the standard deviation and coefficient of variation, yielded the following results:

Tabel 6. SD pH sensor

Location	Mean pH	Standard Deviation	CV (%)	pH Range	Permissible Limit	Status
Garden1	6.48	0.084	1.29%	6.4-6.6	SD≤0.20 pH	Accepted
Garden2	6.72	0.130	1.94%	6.6-6.9	SD≤0.20 pH	Accepted
Garden3	6.66	0.114	1.71%	6.5-6.8	SD≤0.20 pH	Accepted

The pH standard deviation values were below 0.20 pH for all test sites. This indicates that the pH readings were stable over the testing period. The pH sensor readings are stable and within the expected soil pH range for the fuzzy system.

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Ultrasonic Sensor Testing

An ultrasonic sensor is used to detect the water level in the tank. Ultrasonic sensor testing was performed, with the test results shown in Table 7.

Table 7. Ultrasonic Testing

No	Water Conditions	Sensor Distance	Meter Distance (cm)	Difference (cm)	Water Volume (liters)	Reservoir Status	Error Rate (%)
1	Empty	95.2	95.0	0.2	0	Empty	0.21%
2	Half	48.3	48.5	0.2	591.6	Half full	0.41%
3	Full	8.1	8.0	0.1	1,098	Full tank	1.25%
Mean		50.5	50.5	0.17	563.2		0.62%

The ultrasonic sensor error rate was calculated by comparing the sensor distance reading with the manual distance measurement using a meter. The error rate was obtained by dividing the absolute difference between the sensor and reference measurement by the reference measurement, then multiplying by 100%. Based on the test results, the ultrasonic sensor produced error rates of 0.21%, 0.41%, and 1.25% for empty, half-full, and full reservoir conditions, respectively. The average error rate was 0.62%, indicating that the ultrasonic sensor had good accuracy for monitoring reservoir water levels.

$$Error\ Rate = \frac{0.2}{95} x\ 100 = 0.21\%$$

$$Mean\ \ Error = \frac{0.21 + 0.41 + 0.125}{3} = 0.62\%$$

Sensor validation results using Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (4)$$

$$MAE = \frac{1}{3}\sum_{i=1}^{n}|95.2 - 95| + |48.3 - 48.5| + |8.1 - 8.0|$$

$$\mathrm{MAE} = 0.17$$

The MAE of 0.17 cm is far below the permissible limit of 1 cm. The MAPE of 0.62% is also far below the 5% tolerance limit. These values show that the ultrasonic sensor has very good accuracy for reservoir water-level monitoring.

Solar Panel and Solar Charge Controller Testing

The solar panel and solar charge controller testing aim to determine the real-time output voltage produced. The test results are shown in Table 8.

Table 8. Solar Panel Testing

No	Hour	Weather Conditions	Panel Voltage (Multimeter)	Panel Voltage (SCC)	Difference (V)
1	08:00	Cloudy	11.85	11.65	0.20
2	09:00	Cloudy	13.42	13.12	0.30
3	10:00	Sunny	14.15	13.85	0.30
4	11:00	Sunny	14.68	14.38	0.30
5	12:00	Bright	15.35	15.05	0.30
Mean			13.89	13.61	0.28

The solar panel's output voltage went up as the weather got better, rising from 11.85 V on a cloudy morning at 08:00 to 15.35 V in bright sunlight at 12:00. On average, the voltage readings from the multimeter and the solar charge controller differed by just 0.28 V. This small difference shows that the solar charge controller tracks the panel voltage reliably, and the solar panel can support the smart farming system even as sunlight changes.

Sensor validation results using Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (5)$$

$$MAE = \frac{1}{5}\sum_{i}^{n}|11.85 - 11.65| + |13.42 - 13.12| + |14.15 - 13.85|$$

$$\mathrm{MAE} = 0.28$$

The MAE of 0.28 V is below the permissible limit of 0.5 V. The MAPE of 2.01% is also below 5%. Therefore, the solar charge controller voltage reading can be considered sufficiently accurate for monitoring the smart farming energy system.

Table 9. Solar Charge Controller Testing

No	Hour	Input Voltage (Panel)	Output Voltage to Battery	Charging Status
1	08:00	11.85	12.10	Initial Charging
2	09:00	13.42	12.60	Charging
3	10:00	14.15	13.10	Stable Charging
4	11:00	14.68	13.70	Optimal Charging
5	12:00	15.35	13.80	Battery Almost Full
	Mean	13.89	13.06	

For a 12 V battery-based system, an output voltage range of 12.10–13.80 V indicates that the solar charge controller supplied a charging voltage within a reasonable operational range. The output did not exceed 14.4 V, which is commonly used as an upper charging limit for 12 V battery systems. On average, the panel supplied 13.89 V, and the battery received 13.06 V. These results show the controller can handle charging and protect the battery from unstable panel output.

Blynk App Connection Testing

This test aims to detect and identify sensor input and relay output errors in Blynk App operations, enabling the entire system to be monitored and operated in real time.

Figure 11. Blynk Status

Figure 11 displays how the smart farming system is monitored in real time using the Blynk app. The interface shows sensor readings, including temperature and soil humidity, sent from the ESP32 through an IoT connection. This setup proves that the Android-based monitoring system can receive, show, and update field data instantly. As a result, farmers can check the condition of their land directly, without having to measure it by hand, which makes daily farm monitoring easier and more practical.

Fuzzy Logic Testing for Fertilization

Fuzzy logic testing was conducted to verify that the system could provide accurate fertilizer recommendations based on input from pH, soil moisture, and temperature sensors.

Figure 12. Fuzzy Fertilization Testing

This section presents the test results for the fertilization information system that uses fuzzy logic and displays data on the Blynk app. The system takes soil pH, humidity, and temperature as inputs, then uses Sugeno fuzzy logic to determine whether fertilizer is needed. The output tells users whether the plants need fertilization. These results show that the system can convert sensor data into actionable recommendations, helping farmers use fertilizer more accurately and avoid waste.

Table 10. Fuzzy Logic Testing of Fertilization

Table 10 evaluates fertilization decisions based on soil pH, soil moisture, and temperature. The fuzzy outputs were 0.44, 0.25, 0.15, and 0.85. If the system uses a decision threshold of 0.5, then fuzzy results below 0.5 should be assigned to one class, and those above 0.5 should be assigned to the other class. However, the table shows inconsistent interpretation of fuzzy output values.

Using the rule base in Table 1, the decision consistency of Table 10 can be evaluated as follows:

Table 11. Consistency of Fertilization Decisions

Test Case	Input Condition	Expected Rule-Based Status	Status in Table 10	Consistency
1	Acid pH, normal moisture, normal temperature	Fertilized	Not-Fertilized	Not consistent
2	Normal pH, normal moisture, normal temperature	Fertilized	Fertilized	Consistent
3	Alkaline pH, high moisture, warm temperature	Fertilized	Not-Fertilized	Not consistent
4	Acid pH, low moisture, cold temperature	Not-Fertilized	Not-Fertilized	Consistent

A 50% consistency level is below the minimum acceptable decision consistency threshold of 90%. This means that the fertilization decision output is not yet analytically strong.

Fuzzy Logic Testing for Watering

Fuzzy-logic testing was conducted to evaluate the performance of an intelligent, logic-based automated decision-making system for regulating plant watering, based on input from pH, soil moisture, and temperature sensors.

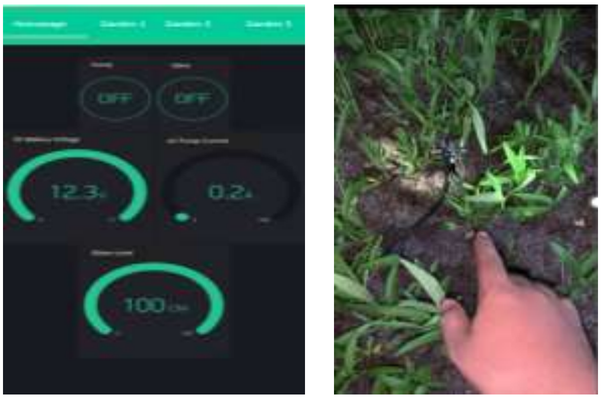

Figure 13. Fuzzy Watering Testing

Figure 13 presents the testing process for the fuzzy logic-based watering system, which uses a Blynk display and measures soil moisture in the field. The system checks soil pH, humidity, and temperature to determine whether to open or close the automatic drip irrigation valve. If the fuzzy logic output indicates that watering is needed, the valve opens to allow water to reach the plants. If the soil is already in good condition, the valve stays closed. These tests show that the watering subsystem can react to real-time field conditions and help use water more efficiently in agriculture.

Table 12. Fuzzy Logic Testing of Watering

No	Soil pH	Humidity (%)	Temperature (°C)	Fuzzy Results	Valve Status	Action
1	6.2 (Acid)	35 (Low)	32 (Warm)	0.80	ON	Valve Open
2	6.8 (Normal)	65 (Normal)	26 (Normal)	0.20	OFF	Valve Closed
3	7.0 (Normal)	75 (High)	25 (Normal)	0.15	OFF	Valve Closed
4	6.5 (Normal)	40 (Low)	29 (Normal)	0.70	ON	Valve Open

Table 12, evaluates watering decisions based on soil pH, humidity, and temperature. The fuzzy results were 0.80, 0.20, 0.15, and 0.70. The valve was ON when the fuzzy output was high and OFF when it was low. Using a threshold of 0.5, the decision rule is:

Fuzzy result ≥ 0.5 = Valve ON

Fuzzy result < 0.5 = Valve OFF

Table 13. Consistency of Fertilization Decisions

Test Case	Fuzzy Result	Expected Valve Status	Actual Valve Status	Consistency
1	0.80	ON	ON	Consistent
2	0.20	OFF	OFF	Consistent
3	0.15	OFF	OFF	Consistent
4	0.70	ON	ON	Consistent

This result shows that the fuzzy watering system is fully consistent with the decision threshold. The system successfully opened the valve when soil moisture was low and closed the valve when soil moisture was normal or high.

IV. Conclusion

The outcomes derived from the design and implementation of artificial intelligence using fuzzy logic in IoT-based agricultural management are as follows:

1. Fuzzy logic is a computational intelligence method, functioning as a good Decision Support System (DSS), with performance capable of providing information for agricultural crop fertilization, based on temperature, humidity, and pH of agricultural soil in real-time.
2. Controlling plant watering through valve settings, using fuzzy logic, produces an automatic watering system based on real-time conditions of temperature, humidity, and pH of agricultural soil.
3. Android, as an IoT information medium, has functioned effectively, providing information on soil temperature, humidity, pH, and fertilization times, allowing for real-time monitoring of agricultural soil conditions.
4. An intelligence-based smart farming system designed to produce appropriate fertilizer recommendations, an automatic watering system based on temperature, humidity, and soil pH, as well as real-time control of the

pump filling the water reservoir from a water source (ground well), so that it can increase soil fertility and optimal plant growth, reduce soil pollution from excessive fertilization, and maximize crop yields.

5. The use of solar panels in this smart farming system can function as an energy source to meet electricity needs and support green energy. Suggestions for developing this IoT-based smart farming system include: Adding weather sensors, such as rain sensors and light intensity sensors, so the system can provide more precise fertilizer or watering recommendations based on weather conditions. Developing an IoT system for remote monitoring or control using a web application, if the agricultural land is extensive and located in various locations.

V. References

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