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Optimization of Rice Field Irrigation Based on Fuzzy Logic and the Internet of Things Through Water Level Analysis

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ABSTRACT

The low efficiency of conventional irrigation systems often results in water waste and decreased rice productivity. The research was carried out by designing an automatic monitoring and control system using a water level sensor, a Raspberry Pi Pico W microcontroller, a water pump, and a Blynk application as a real-time monitoring medium. Water level data is processed by fuzzy logic method to categorize low, normal, or high conditions, so that the system can adjust the water pump adaptively according to the needs of the land. The results of the study show that the integration of IoT and fuzzy logic is able to improve water use efficiency, maintain soil moisture at optimal conditions, and support better rice growth. The system has also been proven to be accurate in the classification of water conditions with a success rate above 90%. Thus, this research contributes to the development of smart agricultural technologies that can increase productivity while supporting sustainable agricultural practices.

I. INTRODUCTION

As an agrarian country, the agricultural sector has an important role in the Indonesian economy. Rice fields as one of the main forms of agricultural land have a significant role in meeting domestic food needs (Firdausi, 2020). However, inefficient management of rice field irrigation is one of the main challenges in increasing agricultural productivity. According to data from the Central Statistics Agency (BPS), around 20-30% of rice fields in Indonesia face water scarcity, especially in the dry season. This shows the need for new, more modern and technology-based approaches to address these challenges.

Conventional irrigation systems are often incapable of providing an even distribution of water according to the needs of the crops. This is due to the lack of real-time data on land conditions, such as water levels and water needs at each point of the rice field. As a result, water is often overused in one area, while other areas suffer from shortages. This problem not only has an impact on the efficiency of water resources but also on suboptimal crop yields. Research shows that data-driven water monitoring and distribution can improve water use efficiency by up to 25%. (Adil & Triwijoyo, 2021).

In the irrigation water distribution process, many manual methods are still used, such as opening and closing water channels by hand by farmers in rice fields. However, this method has many obstacles such as requiring a lot of effort and being less effective. Therefore, it is necessary to apply technology to make the process easier by adopting an automatic control system.

The Internet of Things (IoT) has become an increasingly widely used technology in the agricultural sector to support data-driven systems. IoT enables real-time monitoring of land conditions through sensors connected to the network, providing accurate data for decision-making. The implementation of IoT in irrigation systems has been proven to improve the efficiency of water distribution in various developed countries. In Indonesia, the application of IoT in the agricultural sector is still limited, especially in rice field water management. This potential provides a great opportunity to increase productivity through IoT-based technologies (Sari & Kusumanto, 2024).

In addition to IoT, fuzzy logic offers a solution to address complexity in irrigation decision-making. By processing various parameters such as water level, soil moisture, and plant water needs, a fuzzy-based approach can provide more precise recommendations than conventional methods. Previous research has shown that the combination of fuzzy logic and IoT can improve irrigation efficiency by up to 30%. Therefore, the combination of these two technologies is very relevant to be applied to rice field irrigation systems in Indonesia (Saskia Eka Cahyani et al., 2023).

In the context of rice field irrigation, an integrated approach that combines IoT for monitoring and fuzzy logic for decision-making is a promising solution. The system not only allows for real-time data collection, but also provides automated recommendations for efficient water distribution. With the application of this technology, rice field water management can be carried out more sustainably, reduce water waste, and support agricultural sustainability in the face of increasingly uncertain climate change

Referring to the above problem description, In the context of rice field irrigation, an integrated approach that combines IoT for monitoring and fuzzy logic for decision-making is a promising solution. The system not only allows for real-time data collection, but also provides automated recommendations for efficient water distribution. With the application of this technology, rice field water management can be carried out more sustainably, reduce water waste, and support agricultural sustainability in the face of increasingly uncertain climate change. The water level parameters in this study are the main factors in optimizing rice field irrigation.

The ideal water level of the rice fields contributes to the optimal growth of rice plants by maintaining appropriate soil moisture. If the water is too high, the soil becomes saturated with water which can potentially inhibit root growth and increase the risk of plant diseases due to excess moisture. The effect of water level parameter optimization on crop production is very significant. With an IoT-based and fuzzy automated monitoring and regulation system, rice plants can grow in optimal conditions without experiencing water stress. This has a direct impact on improving crop quality, accelerating growth, and increasing crop yields. The novelty of this research lies in the innovative integration of rice field water level analysis, fuzzy logic, and Internet of Things (IoT) technology to optimize irrigation systems. By utilizing IoT sensors for real-time data collection regarding water levels, the study not only produces accurate elevation maps but also applies fuzzy models to manage uncertainty in irrigation decision-making.

II. METHOD

A. Research Design

This study is a quantitative experimental study designed to develop a field irrigation optimization system based on fuzzy logic and the Internet of Things (IoT) through water level analysis. The research design is illustrated in Figure 1 below:

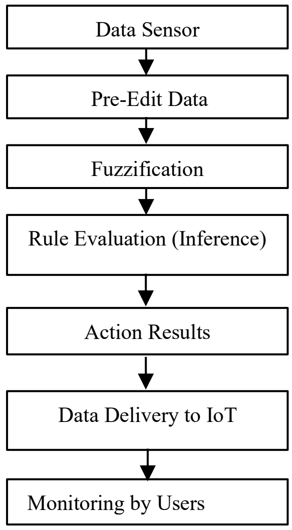


Figure 1 Research Design

1. *Data Sensor*

At this stage, data is collected from various sensors, such as:
   a. Water level sensor
   b. Water flow sensor

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

2. *Pre-Edit Data*

The purpose of this processing is to prepare the data to be suitable for processing. This includes:
   a. Calibration: Adjusts sensor readings to match actual standard values
   b. Filtering: Removes noise from sensor data
   c. Normalization: Converts data to a uniform scale (for example, 0-1)
   d. The result is clean, stable data, ready to use at the fuzzy processing stage.

3. *Fuzzification*

This step involves converting the numerical sensor value to a fuzzy value.
Example:
A water level of 10 cm → is categorized as "normal" with a certain level of membership This process uses membership functions, such as triangle, trapezoidal or gaussian shapes.

4. *Rule Evaluation (Inference)*

It is a decision-making process based on fuzzy rules.
Rules are defined in logical terms, such as:
   a. IF Level = low THEN Pump = ON
   b. IF Level = normal THEN Pump = OFF
   c. IF Level = high THEN Pump = OFF

At this stage, the system combines diverse fuzzy inputs to determine fuzzy outputs based on the rule base

5. *Defuzzification*

The fuzzy output is converted to crips values (exactly).
Example:
Common methods: Centroid, Bisector, Mean of Maximum (MoM)

6. Decision/Action

Based on the results of the defuzzification, the system will: Automatically turn the pump on or off when a certain rice field water level is high

7. Data Delivery to IoT

Decision data, real-time sensor readings, and water level status are transmitted to the IoT platform for remote monitoring and control.

B. Block Diagram

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

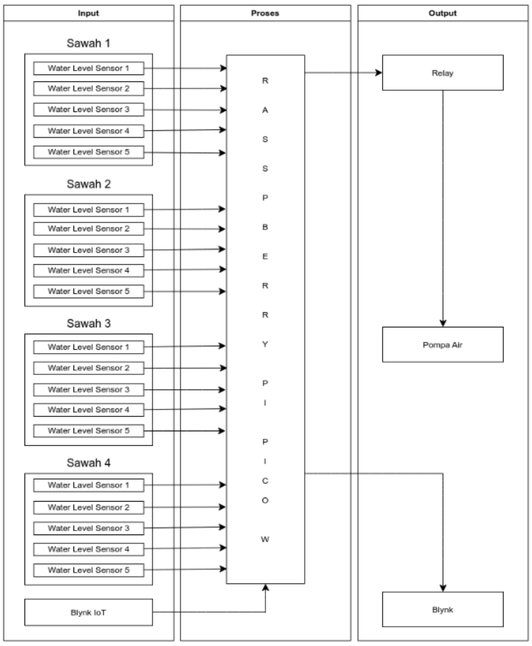


Figure 2. Block Diagram

Figure 2 above is a block diagram that describes the Raspberry Pi Pico W-based rice field water level monitoring and control system. These sensors function to detect the height of water in rice fields in stages. The data from the sensor is then sent to the Process section, which is the Raspberry Pi Pico W microcontroller, which is the control center of the system. The Raspberry Pi Pico W will process sensor data to determine the water conditions in the rice fields. The results of this processing are passed on to the Output section, where the Raspberry Pi Pico W controls the Relay to activate or turn off the Water Pump, so that the water level can be maintained as needed. In addition, this system is also connected to the Blynk IoT application, so users can monitor and control the condition of rice field water remotely via smartphones. Thus, this diagram shows the workflow from sensor detection, data processing, to water pump control actions and monitoring through Blynk.

C. Schematic diagrams.

Figure 3. Schematic Diagram

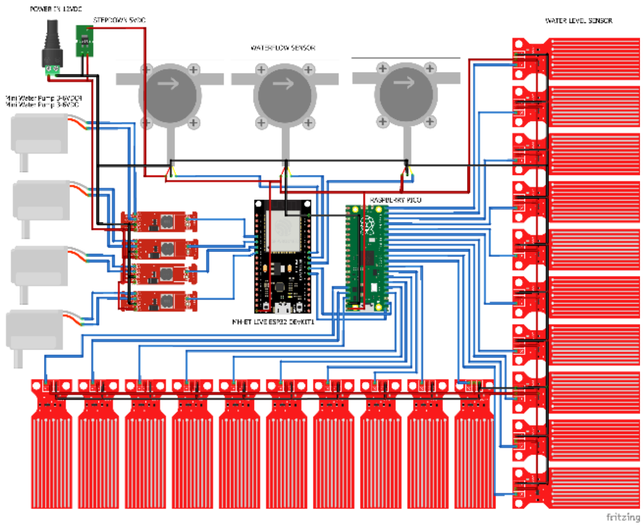


Figure 3 shows a schematic diagram of the system

1. Power Supply
   The system gets a power supply from a 12V DC adapter, then lowered to 5V DC using a step-down module to provide the appropriate voltage to the microcontroller, sensors, and other components
2. Water Level Sensor
   Many water level sensors are installed in parallel (with the input pins of each going into the Raspberry Pi Pico). This sensor detects the height of the water in the rice fields.
3. Water Flow Sensor
   This sensor is installed in the waterway to detect the flow rate. The data obtained will be sent to the Rasppberry Pi Pico W for monitoring.
4. Microcontroller (Raspberry Pi Pico & ESP32)
   a. Raspberry Pi Pico: in charge of reading data from the water level sensor.
   b. ESP32 (MH-ET LIVE ESP32 DEVKIT V1): functions as an IoT link with the Blynk app, receives data from the Raspberry Pi Pico, and sends the sensor status to the cloud for monitoring via smartphone.
5. Relay Module
   There are several relay modules operated by the ESP32. This relay functions as an electronic switch to turn the water pump on or off according to the microcontroller's instructions.
6. Water Pump
   The pump is controlled by a relay to add water to the rice fields/reservoirs if the water level is below the limits specified by the system

D. Fuzzification

Each sensor reading is converted into the corresponding linguistic set:

TABLE 1.
MEMBERSHIP FUNCTIONS

Variable	Linguistic Sets	Membership Function (μ) – example of a core point
Water Levels	Low (0 - 8 cm) | Normal (7 – 14 cm) | Height (12 – 20 cm)	The linear shape descends: μ=1 at 0 cm → decreases to μ=0 at 8 cm. Core points: (0.1), (8.0). Triangle shape: μ=0 at 7 cm → rises to μ=1 at 10 cm → drops to μ=0 at 14 cm. Core points: (7.0), (10.1), (14.0). The linear shape rises: μ=0 at 12 cm → increases to μ=1 at 20 cm. Core point: (12.0), (20.1)

Table 1 above describes the variables of rice field water level which are divided into three linguistic sets, namely Low, Normal, and High, each with a fuzzy membership function. In the Low (0–8 cm) condition, a linear down function is used, where full membership (μ=1) occurs at 0 cm and decreases to μ=0 at 8 cm. For the Normal condition (7–14 cm) a triangle function is used, with μ=0 at 7 cm, increasing to μ=1 at 10 cm as the peak, then dropping again to μ=0 at 14 cm. Meanwhile, in the Height condition (12–20 cm), the linear function rises is used, with μ=0 at 12 cm and gradually increasing to μ=1 at 20 cm. As such, this table illustrates how each water level category is fuzzy modeled through the core points of membership.

E. Membership Functions

1. Water Levels

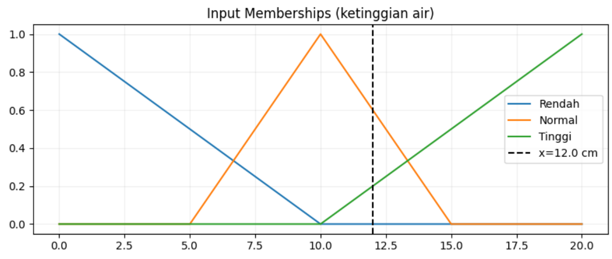


Figure 4. Water Height Graph

Figure 4 is the Water Level Graph showing the water level fuzzy membership function with three categories: Low, Normal, and High. At the point x = 12 cm, the membership of "Normal" begins to decrease, while "High" begins to increase, so that the water condition is between normal and high.

2. Pump

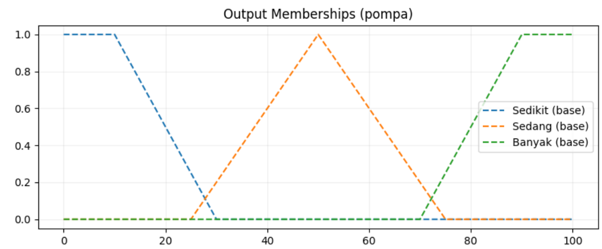


Figure 5. Pump Graphics

Figure 5 is the Pump Graph showing the fuzzy membership function for pump outputs with three categories: Few, Medium, and Many. The horizontal axis represents the intensity of the pump (0–100), while the vertical axis represents the degree of membership (0–1). The pump is slightly active at low values, Medium is in the middle with a peak of around 50, and Lot is active at high values close to 100.

3. Centroid Method

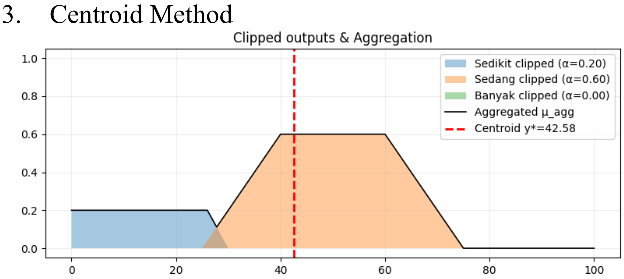


Figure 6. Centroid Method

Figure 6 above shows the fuzzy inference results on the pump output by clipping and aggregation. The Slightly truncated category at 0.20 membership degree, Medium at 0.60, while Many is worth 0. The resulting areas of the cut are then combined to form an aggregate membership function. The dotted red line shows a centroid value of about 42.58, which is the final result of defuzzification to determine the working intensity of the pump.

4. Base Aturam

TABLE 2.
RULE BASE

ID	IF(Condition)	Then (Actuator)
R1	IF Level = Low THEN	Pump ON
R2	IF Level = Normal THEN	Pump OFF
R3	IF Level = THEN High	Pump OFF

The above rule base shows the logic of pump control based on water level conditions. If the water level is low, the pump will turn on (ON) to increase the water supply to the rice fields. On the other hand, if the water level is in normal conditions, the pump will turn off (OFF) because the height is in accordance with the needs of the plant. Likewise, when the water level is high, the pump remains off (OFF) so that there is no excess water that can damage rice growth. With this rule, the irrigation system can maintain the stability of the water level automatically and efficiently. The process starts from dividing input variables into linguistic sets such as Low, Normal, and High, each of which has a membership function. After that, each input condition is set the most appropriate action, for example if the water is low then the pump should be turned on, while if the water is normal or high then the pump is turned off.

III. RESULTS AND DISCUSSION

A. Result

1. System Implementation Summary

This research has resulted in an Internet of Things (IoT)-based rice field irrigation monitoring system that integrates with fuzzy logic.

a. Water Level Sensor
b. Raspberry Pi Pico W Microcontroller
c. Blynk platform for real-time monitoring
d. Fuzzy logic algorithm for classification of rice field irrigation through water level and action recommendations.

The system is installed in the agricultural experimental fields with 20 sensor points. Data acquisition is automated.

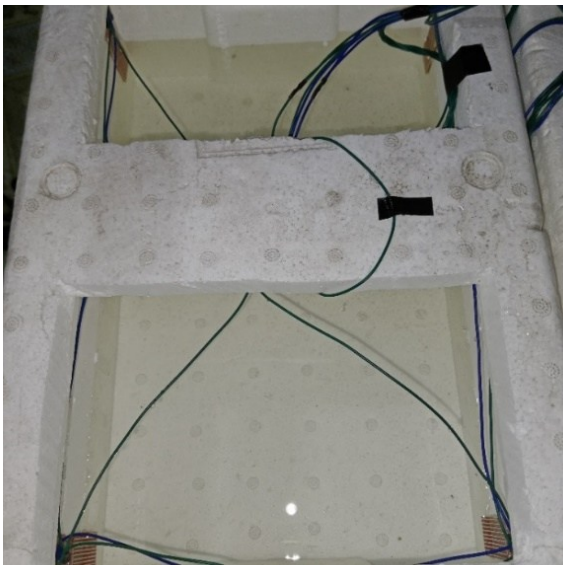


Figure 7. Rice Field Prototype

In the image above, you can see a container (using a styrofoam box) containing water, with several sensor cables attached to it. The cables are water level sensors installed at 5 different height points. The function of this sensor is to detect the height of the water level in the container. Each cable represents one level, from the lowest level to the top. When water touches the end of a particular sensor cable, a microcontroller (Raspberry Pi Pico W) reads the signal to know that the water has reached that height. With 5 sensor levels, the system can find out the water condition starting from empty, low, normal, high, so that the pump can be turned on or off automatically as needed.

2. Software Testing

The system is installed in agricultural experimental rice fields with 20 sensor points in 4 rice fields. Data acquisition is automated. One example is as follows.

Figure 8. Computer Monitor Display 1

The image above shows a digital rice field monitoring display. On the left side there is a graph of changes in the condition of the rice fields from time to time, while on the right side there is an indicator of water volume of 1 705.3 liters and a water height of 17.25 cm. This data shows that the system can monitor the amount and level of water in real-time to support irrigation management.

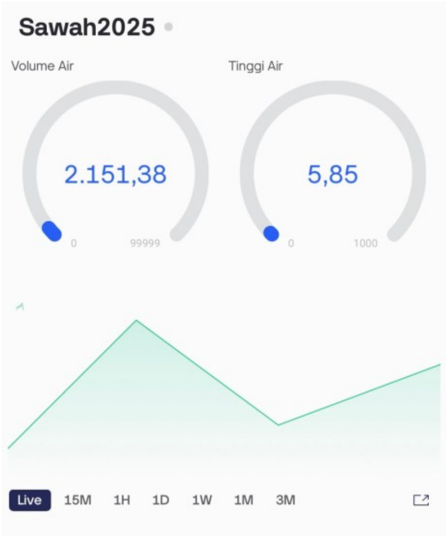


Figure 9. A Display of Cell Phone Monitors 1

The image above shows a dashboard for monitoring the condition of rice fields called Sawah2025. There are two main indicators, namely Water Volume of 2,151.38 liters and Water Height of 5.85 cm, which are displayed with a gauge model to facilitate reading. At the bottom is a line graph that represents changes in data in real-time with different time range options, ranging from 15 minutes to 3 months. This view shows that the system is designed to monitor and analyze water conditions in rice fields directly to support more efficient irrigation management.

3. Descriptive Data

TABLE 3.
DESCRIPTION DATA

Category	Count	Min	Max	Mean	Median	Std
Usual	21605	8.00	14.00	10.976268	10.96	1.739916
Low	28296	0.00	7.99	3.992317	3.96	2.316750
Tall	21615	14.01	20.00	17.005080	17.01	1.728844

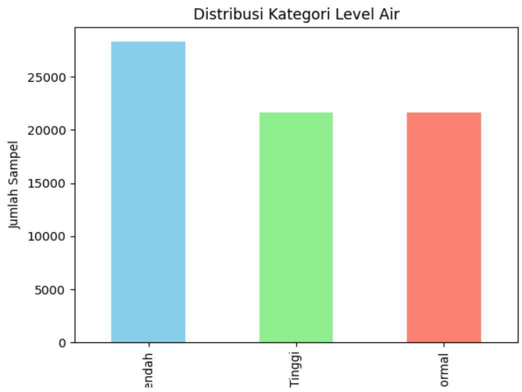
Table 3 above displays the descriptive water height data which is grouped into three categories, namely Normal, Low, and High.

a. The Normal category consists of 21,605 data with a water height range of 8.00 – 14.00 cm. The average water height was 10.98 cm, the median value was 10.96 cm, and the standard deviation was 1.74, which means that the data was relatively more uniform than the low category.
b. The Low category has the largest number of samples, namely 28,296 data with a water height range between 0.00 – 7.99 cm. The mean water height in this category is around 3.99 cm, with a median value of 3.96 cm and a standard deviation of 2.32, which indicates a considerable variation in the data in this category.
a. The Height category has 21,615 data with a water height range of 14.01 – 20.00 cm. The average water height was recorded at 17.01 cm, the median was 17.01 cm, and the standard deviation was 1.73, indicating that the data spread was also quite stable as the normal category

4. System Reading Analysis

The graph above shows the distribution of water level categories based on the number of samples observed. There are three categories displayed, namely Low, High, and Normal. From the graph, it can be seen that the Low category has the most number of samples, which is close to 28,000 samples

Meanwhile, the High and Normal categories have almost the same number of samples, about 21,500 samples each. This shows that water conditions are more often at low levels compared to normal or high levels.



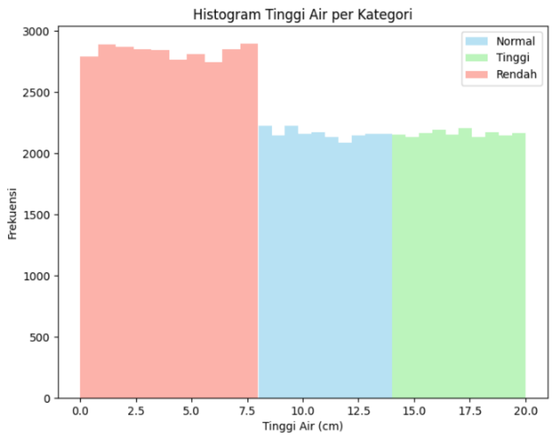


Figure 11. Water Height Histogram

Figure 11 above shows the height distribution of water divided into Low, Normal, and High categories. The Low (0–7.5 cm) category has the highest data frequency, while the Normal (7.5–15 cm) and High (15–20 cm) categories have the lowest and almost balanced frequencies. This shows that the water level is more often in the low category.

5. Model Evaluation

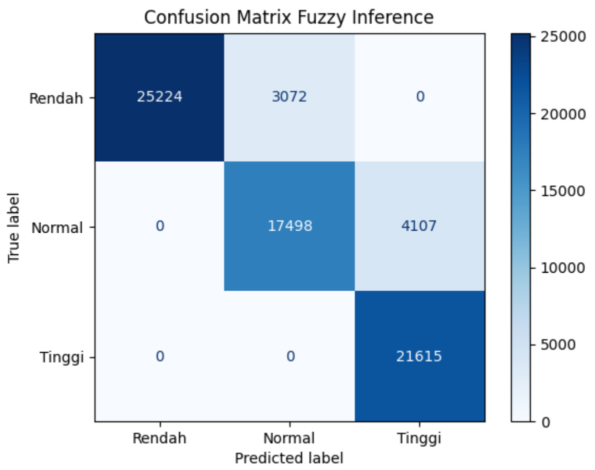


Figure 12. Model Evaluation

Overall, the model had a total accuracy of 0.90 (90%) from 71,516 sample data. The macro average and weighted average values for precision, recall, and F1-score are all in the range of 0.90 which means the model's performance is balanced across all categories.

Figure 12 above is a confusion matrix resulting from the *Fuzzy Inference* method for the classification of water levels into three categories, namely Low, Normal, and High. On the vertical axis is displayed the true *label*, while on the horizontal axis the *predicted label* is displayed

From the graph it can be seen that:

a. The Low category data was mostly classified as correct, namely 25,224 samples were predicted as low, but there were 3,072 samples that were incorrectly predicted as normal.
b. The data of the Normal category has 17,498 samples that are predicted to be correct, but there are still misclassifications, namely 4,107 samples are predicted to be high.
c. The high-category data was fully correctly classified, i.e. 21,615 samples without any prediction errors.

B. Discussion

Overall, the model had a total accuracy of 0.90 (90%) from 71,516 sample data. The macro average and weighted average values for precision, recall, and F1-score are all in the range of 0.90 which means the model's performance is balanced across all categories.

Based on the results of the fuzzy inference test on the water level data of the rice fields (maximum 20 cm), the confusion matrix was obtained as follows:

a. Low Class
   a) 25,224 data were correctly detected as Low.
   b) 3,072 data were misclassified as Normal.
   c) There is no wrong data to the High class.

The accuracy rate of the Low class is very high (> 89%), only a small percentage of it shifts to the Normal class.

b. Normal Class
   a) 17,498 data detected as Normal.
   b) 4,107 data were incorrectly classified as High.
   c) There is no wrong data to the Low class.

The Normal class experienced weakness as about 19% of the data shifted to the High class. This indicates a fuzzy overlap of membership functions between Normal and High.

c. High class
   21,615 data is fully detected correct as high

No misclassification

High grade accuracy reaches 100%, indicating the system is very consistent in detecting high water conditions.

From the above results, it can be concluded that:

a. The overall accuracy is very high, with a classification success rate above 90%.
b. Low and High grades read very well, so the fuzzy rules in these two categories can be considered optimal.
c. The Normal class is still prone to misclassification, especially when the water level is close to the boundary between the Normal and High categories. This is understandable because physically, sensor values under "normal" conditions are often close to the threshold of "high".

The fuzzy inference system is reliable for real-time monitoring of rice field irrigation. Errors in the Normal class need to be addressed so that irrigation decision-making is more precise, for example by shifting or adjusting the shape of the membership function. With high accuracy results, the system can assist farmers in determining when fields need to be irrigated (if the water is low), maintained (if normal), or stopped (if high).

IV. CONCLUSION

This research successfully designed and implemented a field irrigation optimization system based on fuzzy logic and the Internet of Things (IoT) by utilizing water level sensors, Raspberry Pi Pico W microcontrollers, water pumps, and Blynk applications as monitoring media. The system built is able to work automatically in regulating water distribution according to rice field conditions through the classification of water levels into three linguistic categories, namely low, normal, and high.

The test results showed that the system had a high level of accuracy, with an average accuracy of up to 90%, where the low and high categories were detected very well, while the normal category still showed a slight weakness due to the overlap with the high category. This proves that the application of fuzzy logic is effective in handling the uncertainty of sensor data and is reliable for real-time irrigation decision-making.

Overall, this system is able to support the research objectives, which are:

1. Designing a fuzzy logic and IoT-based rice field water level analysis tool that can monitor conditions in real-time.
2. Testing and proving system performance, with classification accuracy results above 90% and pump control functions running according to fuzzy rules.
3. Determine the optimal sensor placement, namely five points (four corners and one in the middle), so that the reading results are more representative of the condition of the rice fields.

Thus, the integration of IoT and fuzzy logic in the rice field irrigation system has been proven to improve water use efficiency, reduce waste, facilitate monitoring, and support sustainable agricultural practices oriented towards increasing rice productivity

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