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Internet of Things-Based Water Quality Monitoring and Automatic Feeding for Catfish Ponds Using Mamdani Fuzzy Logic

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Abstract

Manual water-quality monitoring and schedule-based feeding may delay responses to unsuitable pond conditions and lead to inappropriate feed dispensing in catfish cultivation. This study developed an Internet of Things (IoT)-based monitoring and automatic feeding system that evaluates water temperature and pH using Mamdani fuzzy inference. The prototype integrates an ESP32 microcontroller, temperature and pH sensors, an ultrasonic sensor for feed-level monitoring, and a servo motor for feed dispensing. Temperature and pH measurements are classified into five linguistic categories and evaluated through a 25-rule base to produce a binary Feed ON or Feed OFF decision. Sensor validation yielded accuracies of 95.52% for temperature measurement, 95.87% for pH measurement, and 95.97% for ultrasonic distance measurement. Validation using five representative input combinations showed that all program outputs matched the expected rule-base decisions, resulting in 100% decision conformity for the tested cases. During seven days of field monitoring, all 21 evaluations conducted at 09:00, 15:00, and 21:00 produced Feed ON because the paired temperature and pH measurements satisfied the minimum rule-base requirements. Web and mobile dashboards displayed sensor measurements, feed availability, device status, operating mode, and feeding activity in real time. The main contribution is a compact and interpretable mechanism that performs condition-based feeding decisions locally on the ESP32 while supporting remote supervision through IoT interfaces. The results indicate adequate sensor performance and consistent fuzzy decision implementation under the tested conditions.

Keywords: Water Quality Monitoring; Automatic Fish Feeding; Fuzzy Logic; Internet of Things; Real-Time Monitoring and Control

1. INTRODUCTION

Catfish cultivation contributes to aquaculture production and provides an important source of income for small-scale farmers. Its productivity, however, depends on suitable water conditions and appropriate feeding management. Water temperature and pH influence fish metabolism, physiological condition, appetite, and growth, while excessive or poorly timed feeding can increase feed waste and accelerate water-quality deterioration [1], [2]. In many small-scale farms, these parameters are still monitored manually, and feeding is commonly performed according to fixed schedules without considering current pond conditions. This practice may delay the detection of unsuitable water quality and allow feeding to continue when environmental conditions are unfavorable. Internet of Things-based sensing and automatic feeding technologies offer a practical alternative by enabling continuous measurement, local data processing, actuator control, and remote supervision [3].

Internet of Things technology has been widely applied to improve the continuity and accessibility of aquaculture monitoring. Chen et al. [4] developed a fish-farm monitoring system capable of measuring temperature, pH, dissolved oxygen, and water level and transmitting the data through a wireless network. Shete et al. [5] proposed a real-time water-quality monitoring method that integrated sensing units and communication modules for continuous data acquisition. These studies demonstrated the effectiveness of Internet of Things technology for remote monitoring, although their main contribution was directed toward data collection and transmission rather than automatic feeding decisions. Nagothu et al. [6] extended the monitoring function by incorporating fuzzy logic for water-quality management and pond control. Nevertheless, their system used different input parameters and broader environmental control objectives, whereas an automatic feeder requires a direct assessment of whether current pond conditions are suitable for feed dispensing.

Fuzzy logic has also been implemented in low-cost aquaculture systems because it can translate numerical sensor measurements into interpretable linguistic conditions. Prafanto et al. [7] developed a Sugeno-based water-quality control system for tilapia cultivation using temperature and pH sensors connected to an ESP32. Although the study showed that fuzzy processing could be executed on a resource-constrained microcontroller, its output was intended for water-quality regulation rather than feeding eligibility. Sugiarto et al. [8] introduced an ESP32-based monitoring platform for koi cultivation and displayed water-quality measurements through a cloud dashboard. Subowo et al. [9] similarly developed a low-cost monitoring system for rural aquaculture using pH, total dissolved solids, and temperature sensors. Both systems supported remote observation, but neither focused on a binary fuzzy decision that directly controlled automatic feed dispensing.

Automatic feeding research has introduced more adaptive mechanisms based on fish condition, growth, and feeding behavior. Aljehani et al. [10] examined the relationship between feeding control, water-quality monitoring, and bioenergetic fish-growth models, showing that feeding performance is closely associated with environmental and biological factors. Adegboye et al. [11] developed an intelligent feeding system that dispensed feed according to fish feeding intensity. Although behavior-based approaches can improve feeding adaptability, they often require additional sensors, imaging systems, or behavioral observations that increase implementation complexity. Other studies have employed aquaponic monitoring platforms [12], intelligent buoy systems [13], cloud-based Firebase infrastructures [14], and data-fusion models based on deep reinforcement learning [15]. These developments demonstrate substantial progress

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in smart aquaculture, but their hardware and computational requirements may be less practical for small-scale farms that primarily need dependable monitoring and a clear feeding decision.

Recent reviews have further emphasized the importance of reliable sensing and communication technologies in aquaculture applications. Flores-Iwasaki et al. [16] reported that Internet of Things sensors can improve the surveillance of physicochemical water parameters, although practical integration between monitoring, control, and decision support remains necessary. Akhter et al. [17] noted that advances in low-cost sensor technology have increased the feasibility of continuous water-quality observation in smart fisheries. Singh et al. [18] also highlighted the role of wireless sensor networks in transmitting real-time measurements and supporting timely responses to environmental changes. These findings indicate that the technical components required for smart monitoring are increasingly accessible, but the collected measurements must still be converted into operational decisions that can be executed reliably on embedded devices.

Water temperature and pH were selected as the fuzzy input variables in this study because they are accessible parameters with direct relevance to catfish condition and feeding response. Temperature variation can affect metabolic activity and appetite, while unsuitable pH may cause physiological stress and reduce growth performance. Previous studies have shown that water-quality conditions contribute to catfish survival, development, and production outcomes [19], [20]. Although dissolved oxygen, ammonia, salinity, and turbidity may affect aquaculture performance, incorporating numerous parameters increases hardware requirements and system complexity. Therefore, this study limits the fuzzy model to water temperature and pH, while an ultrasonic sensor is used separately to monitor the feed level.

Based on the reviewed literature, three research gaps remain. First, many Internet of Things-based aquaculture systems focus primarily on monitoring and data transmission without directly linking measured water conditions to automatic feeding eligibility. Second, previous fuzzy-based studies generally address water-quality regulation, apply different fish species, or use control variables that are not specifically designed for binary feed dispensing in catfish ponds. Third, several intelligent feeding methods depend on behavioral sensors, image-processing equipment, or computational models that may be difficult to implement in small-scale cultivation. These limitations indicate the need for a compact system that can evaluate current water conditions, execute an interpretable feeding decision locally, monitor feed availability, and provide remote supervision without relying on external computation for the main control process.

This study aims to develop an Internet of Things (IoT)-based monitoring and automatic feeding system for catfish ponds using Mamdani fuzzy inference. Water temperature and pH are classified into the linguistic categories Very Poor, Poor, Fair, Good, and Optimal and evaluated through a 25-rule base to generate a binary Feed ON or Feed OFF decision. Predetermined feeding times serve as evaluation points, while the fuzzy output determines whether feed dispensing is permitted under the measured pond conditions. An ultrasonic sensor monitors feed availability separately from the fuzzy inference process, and the ESP32 performs sensing, decision-making, and servo control locally. Web and mobile dashboards provide access to sensor measurements, operating status, feed level, and feeding activity. The novelty of this research lies in the integration of local Mamdani-based water-condition evaluation, scheduled binary feeding eligibility, separate feed-level monitoring, and Internet of Things supervision within a compact ESP32-based prototype for small-scale catfish cultivation. The contribution is an interpretable and computationally lightweight decision mechanism that extends aquaculture monitoring from passive presentation to condition-based automatic feeding control.

2. RESEARCH METHODOLOGY

2.1 Research Stages

This research employed a quantitative experimental approach to design and evaluate an Internet of Things-based water quality monitoring and automatic fish feeding system using fuzzy logic. The system was developed to monitor water temperature, pH, and feed availability. Water temperature and pH were used as fuzzy input variables for determining feeding decisions, while feed availability was monitored separately using the ultrasonic sensor. Figure 1 presents the overall workflow from sensor acquisition to fuzzy decision-making and transmission to the monitoring platform.

Figure 1. Research Stages

a. Sensor Data
Sensor data acquisition was performed to obtain real-time information on pond conditions and feed availability. The pH sensor measured the acidity level of the water, the temperature sensor monitored changes in water temperature, and the ultrasonic sensor estimated the remaining feed level in the container. The collected measurements were still raw and could contain short-term fluctuations caused by sensor noise or environmental conditions.

b. Data Preprocessing
Data preprocessing was conducted to improve the reliability of sensor readings before fuzzy logic processing. This stage included calibration to align sensor outputs with reference values and filtering to reduce short-term fluctuations in the sensor readings. The processed water temperature and pH data were then used as stable inputs for the fuzzy inference system.

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c. Fuzzification
Fuzzification converts calibrated temperature and pH measurements into membership degrees on a 0–1 scale. Each input variable is represented by five linguistic quality categories: Very Poor, Poor, Fair, Good, and Optimal. Gaussian membership functions provide smooth transitions between neighboring conditions and allow a measurement to possess partial membership in more than one category [6], [21]. This formulation accommodates uncertainty and variation in sensor readings without imposing rigid classification boundaries.
d. Rule Evaluation
Rule evaluation processes the fuzzified temperature and pH values using a rule base consisting of 25 IF–THEN statements. Both input variables are divided into five linguistic categories, namely Very Poor, Poor, Fair, Good, and Optimal, covering all possible combinations of water conditions. The antecedents of each rule are connected through the fuzzy AND operator, while the firing strength is determined by selecting the minimum membership degree of the corresponding temperature and pH categories [22]. This value represents how strongly the measured conditions satisfy the rule. Since adjacent membership functions overlap, more than one rule may be activated simultaneously, with each rule contributing at a different strength. Each rule produces either Feed ON or Feed OFF. This structure provides a transparent and consistent basis for evaluating feeding suitability under varying pond water conditions.
e. Defuzzification
Defuzzification converts the aggregated output of the Mamdani fuzzy inference process into a single crisp value. The implication strength of each active rule is applied using the minimum operator, and the resulting output sets are combined through maximum aggregation. The centroid method determines the crisp value from the aggregated membership area [22]. Outputs below 0.5 indicate Feed OFF, while those equal to or above 0.5 indicate Feed ON.
f. Decision/Action
At the predetermined feeding time, the servo motor dispenses feed only when the measured water temperature and pH indicate suitable pond conditions. This control mechanism prevents feeding under unfavorable conditions and improves the reliability, safety, and consistency of the automatic feeding process.
g. Data Delivery to IoT
The system transmits feeding decisions, real-time sensor measurements, and feed-level information to the Internet of Things platform, enabling remote monitoring and control through the dashboard interface while supporting timely supervision, operational transparency, and reliable user responses to changing pond conditions.

2.2 Block Diagram

The proposed system was developed to support real-time water quality monitoring and automatic feeding control for catfish pond management. The system integrates sensors, an ESP32 microcontroller, fuzzy logic processing, a servo motor, and an IoT platform to evaluate pond conditions, determine feeding decisions, and provide remote monitoring.

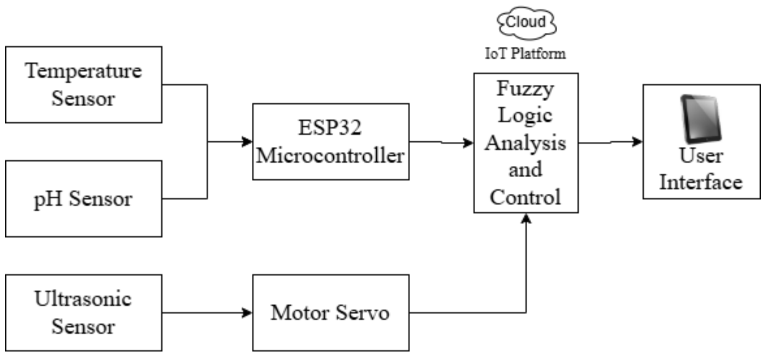

Figure 2. Block Diagram

Figure 2 illustrates the system architecture and the functional relationship among its components. The temperature and pH sensors transmit water quality measurements to the ESP32, where the data are processed through the fuzzy logic control module to determine whether the pond conditions are suitable for feeding. The ultrasonic sensor separately provides distance measurements for estimating the remaining feed level and does not participate in the fuzzy inference process. The feeding decision produced by the fuzzy logic system is used by the ESP32 to control the servo motor according to the feeding schedule. All sensor measurements and system states are transmitted to the Blynk IoT platform, enabling remote monitoring through web and mobile interfaces.

2.3 Schematic Diagram

The schematic diagram presents the hardware layout of the proposed system, showing how the sensing units, ESP32 microcontroller, servo actuator, and Internet of Things platform are integrated to support real-time water quality monitoring and automatic feeding control in catfish pond management. Through this schematic design, the relationship between each component in the system can be clearly understood.

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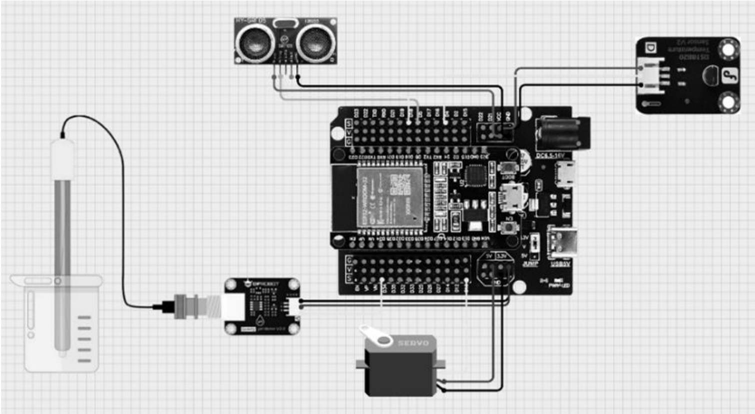

Figure 3. Schematic Diagram

Figure 3 illustrates the hardware schematic and component connections of the proposed system.

a. Power Supply
   The system was powered via USB through the ESP32 microcontroller, supplying the required voltage to the sensors, servo motor, and supporting components.
b. Ultrasonic Sensor
   The ultrasonic sensor is connected to the ESP32 to estimate the remaining feed level in the container. The measured distance data are transmitted to the ESP32 for feed-level monitoring.
c. Water Temperature Sensor
   The temperature sensor measures the thermal condition of the pond water, and its readings are sent to the ESP32 for real-time monitoring and further processing.
d. Water pH Sensor
   The pH sensor is used to measure the acidity level of the pond water. The sensor output is processed by the ESP32 to determine the water condition based on the predefined parameters.
e. ESP32 Microcontroller
   The ESP32 functions as the main controller that reads all sensor measurements, processes water temperature and pH through the fuzzy logic model, monitors feed-level data separately, controls the servo motor, and transmits system information to the IoT platform.
f. Servo Motor
   The servo motor is used as an automatic fish feeding actuator controlled directly by the ESP32 according to the fuzzy logic decision and the predefined feeding schedule.

2.4 Fuzzification

Fuzzification was applied to convert calibrated water temperature and pH measurements into membership degrees ranging from 0 to 1. The universe of discourse was defined as 0–14 for pH and 0–50 °C for water temperature. Each input variable was represented by five linguistic categories: Very Poor, Poor, Fair, Good, and Optimal. Gaussian membership functions were used to provide smooth transitions between adjacent conditions and to represent uncertainty in sensor measurements without imposing rigid classification boundaries [21].

Table 1. Membership Function

Variable	Fuzzy Category	Reference Range Description
pH	Very Poor (< 4.5 and > 9.5) Poor (4.5–5.0 and 9.0–9.5) Fair (5.0–6.0 and 8.0–9.0) Good (6.0–6.5 and 7.5–8.0) Optimal (6.5–7.5)	Gaussian membership functions were defined across the pH domain of 0–14. The Optimal function was positioned within the reference region of pH 6.5–7.5. Paired Gaussian functions represented the Good, Fair, Poor, and Very Poor conditions on the acidic and alkaline sides of the input domain.
Temperature	Very Poor (< 19 °C and > 38 °C) Poor (19–21 °C and 36–38 °C) Fair (21–23 °C and 34–36 °C) Good (23–25 °C and 32–34 °C) Optimal (25–32 °C)	Gaussian membership functions were defined across the water temperature domain of 0–50 °C. The Optimal function was positioned within the reference region of 25–32 °C. Paired Gaussian functions represented the Good, Fair, Poor, and Very Poor conditions on the lower and upper sides of the input domain.

Table 1 presents the linguistic categories and membership ranges assigned to both input variables. The overlapping ranges allow a single measurement to possess different membership degrees in adjacent categories, providing a more realistic representation of continuous variations in pond water temperature and pH.

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2.5 Membership Function

Membership functions define how numerical pH and water temperature measurements are represented as linguistic categories within the fuzzy model. Gaussian functions were used to assign membership degrees ranging from 0 to 1. The overlapping regions between adjacent functions allow gradual transitions between water-quality conditions, preventing abrupt classification changes near category boundaries [21]. The five linguistic categories are represented by nine component functions because the Good, Fair, Poor, and Very Poor categories are modeled separately on the lower and upper sides of the central Optimal condition. Figures 4 and 5 present the pH and temperature membership models.

2.5.1 pH Membership Function

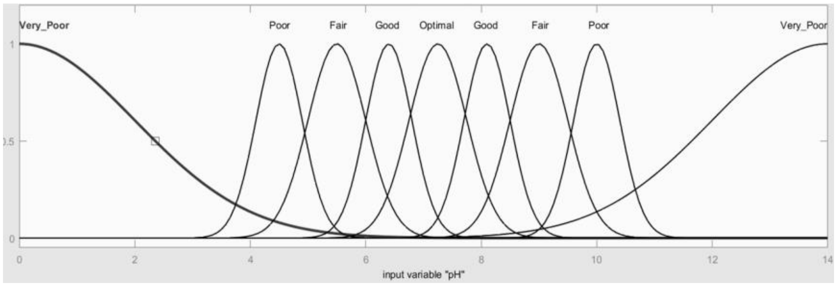

Figure 4. Fuzzy Classification Model for Water pH

Figure 4 presents the membership functions used to classify water pH conditions. The pH input domain ranges from 0 to 14 and is divided into five linguistic categories: Very Poor, Poor, Fair, Good, and Optimal. The Optimal category represents the most suitable pH condition, while values moving toward acidic or alkaline regions are gradually classified into lower-quality categories. The overlapping curves enable pH measurements near category boundaries to hold partial membership in more than one linguistic set, providing a more realistic representation of changes in pond water acidity.

2.5.2 Water Temperature Membership Function

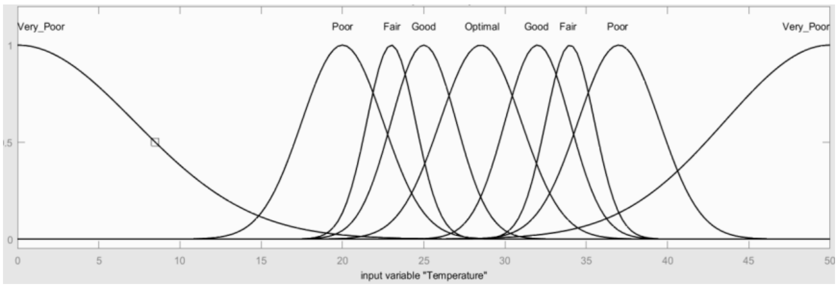

Figure 5. Fuzzy Classification Model for Water Temperature

Figure 5 illustrates the membership functions used to represent pond water temperature conditions. The temperature input domain ranges from 0 to 50 °C and is classified into Very Poor, Poor, Fair, Good, and Optimal categories. The Optimal category represents the most suitable temperature range for catfish cultivation, while lower or higher values gradually shift toward less suitable conditions. The overlapping Gaussian curves reflect continuous temperature variation and allow measurements near category boundaries to be interpreted without relying on rigid classifications.

2.6 Rule Base

The rule base defines the relationship between the linguistic conditions of water temperature and pH and the corresponding feeding decision. The rules are formulated as IF–THEN statements, with the input conditions serving as antecedents and the resulting control action serving as the consequent [22]. In this study, each input variable is divided into five categories, namely Very Poor, Poor, Fair, Good, and Optimal, producing 25 possible combinations.

Table 2. Fuzzy Rule Base Matrix

Temperature/pH	Very Poor	Poor	Fair	Good	Optimal
Very Poor	OFF	OFF	OFF	OFF	OFF
Poor	OFF	OFF	OFF	OFF	OFF
Fair	OFF	OFF	ON	ON	ON
Good	OFF	OFF	ON	ON	ON
Optimal	OFF	OFF	ON	ON	ON

The rule base shown in Table 2 represents the decision-making logic for automatic fish feeding based on water quality conditions. The feeding system produces a binary output consisting of ON and OFF states. Feeding is allowed

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when both temperature and pH are classified as Fair, Good, or Optimal, indicating that the pond water conditions remain suitable for feeding activities. Conversely, feeding is suspended whenever either temperature or pH falls into the Poor or Very Poor category, as unfavorable water quality conditions may negatively affect fish health and feeding behavior. The fuzzy inference process begins by classifying the input variables into linguistic terms, namely Very Poor, Poor, Fair, Good, and Optimal, where each category is represented by a corresponding membership function. These fuzzy sets are then evaluated using the rule base to determine the feeding decision according to the current pond conditions.

2.7 Defuzzification

The Mamdani fuzzy inference method was used to convert the aggregated fuzzy output into a crisp feeding decision. The output variable was defined within the range of 0 to 1 and represented by two overlapping trapezoidal membership functions, namely Feed OFF and Feed ON. The minimum operator was applied during implication, while the outputs of all active rules were combined using maximum aggregation. The centroid method was then used to determine the crisp value from the resulting aggregated membership area [22].

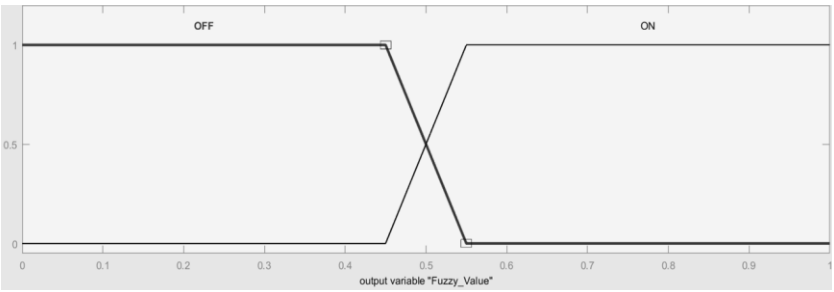

Figure 6. Fuzzy Output Membership Functions

Figure 6 shows the output membership functions used to represent the two feeding conditions. Feed OFF occupies the lower output region, whereas Feed ON represents the higher region. The overlapping area provides a gradual transition between the two decisions and avoids an abrupt change near the decision boundary. The centroid result is interpreted using a threshold of 0.5, where values below 0.5 indicate Feed OFF, while values equal to or greater than 0.5 indicate Feed ON.

3. RESULT AND DISCUSSION

3.1 System Implementation

The implementation of the proposed system was conducted by assembling the main hardware components and integrating them with the control program embedded in the ESP32 microcontroller. This stage was carried out to ensure that each module, including the sensors, actuator, feed container, and monitoring interface, could operate as a unified prototype before sensor validation and dashboard testing were performed. The implementation demonstrated the integration between data acquisition, fuzzy logic processing, feeding control, and Internet of Things-based data transmission.

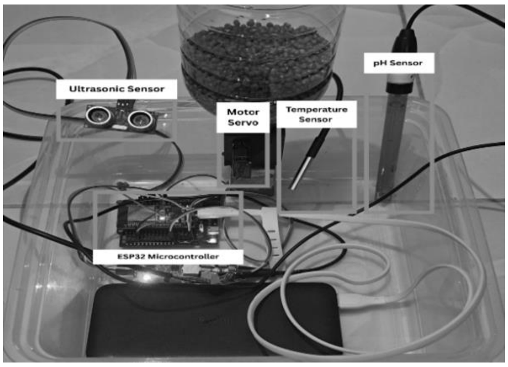

Figure 7. System Implementation

Figure 7 presents the implemented prototype of the Internet of Things-based catfish water monitoring and automatic feeding system. The prototype consists of an ESP32 microcontroller, pH sensor, temperature sensor, ultrasonic sensor, servo motor, and feed container. The pH and temperature sensors were used to measure the pond water parameters, while the ultrasonic sensor was positioned above the feed container to estimate feed availability based on distance measurement. The servo motor was installed near the feed outlet mechanism to control feed dispensing according to the fuzzy logic decision.

The ESP32 microcontroller serves as the central processing unit of the system. It receives sensor readings, processes pH and temperature values through the fuzzy inference system, controls the servo motor, and transmits

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monitoring data to the Internet of Things dashboard. The fuzzy logic algorithm was embedded directly in the ESP32 program, allowing the system to generate feeding decisions locally without requiring external computation. The decision output was designed in binary form, namely Feed ON and Feed OFF, to determine whether feeding should be activated under the measured water quality conditions.

The monitoring interface was implemented through web and mobile dashboards to display water temperature, pH value, remaining feed level, device status, automatic mode, and feeding decision in real time. A manual feeding feature was also provided to allow user intervention when needed. Through this implementation, the developed prototype was able to function as an integrated monitoring and control system for smart catfish aquaculture management.

3.2 Sensor Testing

Testing was conducted on the sensors in the system using five data points. Next, the average error was calculated as a percentage, and then calculations were performed to determine the sensor's accuracy. The results of the temperature test on the DS18B20 sensor are shown in Table 3.

Table 3. Temperature Sensor Testing

Test	Temperature Sensor Value (°C)	Thermometer Value (°C)	Error (%)
1	21.11	20	5.55
2	22.91	22	4.14
3	25.34	24	5.58
4	27.43	26	5.50
5	28.46	28	1.64
Average Error			4.48

$$Percentage\ Error = \frac{|Sensor\ Reading - Reference\ Reading|}{Reference\ Reading}\ x\ 100\% \quad (1)$$

$$Accuracy\ (\%) = 100\% - \ Average\ Error\ (\%) \quad (2)$$

Based on the tests conducted on the DS18B20 temperature sensor, an average error of 4.48% was obtained, and the accuracy rate reached 95.52%. The temperature sensor was capable of measuring temperature accurately within the tested range.

Table 4 shows the results of five tests performed on the PH4502-C sensor. The tests were run to measure accuracy and average reading error.

Table 4. pH Sensor Testing

Test	pH Sensor Value	pH Meter Value	Error (%)
1	3.53	4.01	11.97
2	6.78	6.86	1.18
3	7.32	7.00	4.57
4	9.11	9.18	0.76
5	10.23	10.01	2.20
Average Error			4.13

The PH4502-C sensor achieved 95.87% accuracy with an average error of 4.13%. The sensor demonstrated adequate measurement performance within the tested range.

Table 5 shows the results of five tests conducted on the ultrasonic sensor. The tests were performed to evaluate the sensor's distance measurement accuracy and determine the average percentage error between the measured distances and the sensor readings.

Table 5. Ultrasonic Sensor Testing

Test	Sensor Distance (cm)	Actual Distance (cm)	Error (%)
1	9.21	10	7.90
2	11.27	12	6.08
3	14.4	14	2.86
4	15.74	16	1.63
5	17.7	18	1.67
Average Error			4.03

The ultrasonic sensor's testing results showed an average error of 4.03%, with an accuracy level of 95.97%. The ultrasonic sensor was capable of measuring distance values accurately and consistently. As a result, the sensor displayed excellent accuracy when monitoring the feed level in the container. Throughout the testing phase, all sensors in the system demonstrated excellent performance and accuracy.

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3.3 Software Testing

Software testing was conducted to evaluate the ability of the web and mobile dashboards to receive, update, and present information transmitted by the ESP32. The evaluated functions included water temperature and pH monitoring, feed-level visualization, device connectivity, operating mode, feeding status, and manual feeding control. This stage focused on the accessibility and presentation of system information, while the numerical consistency of the fuzzy logic model was examined separately in the fuzzy decision validation section.

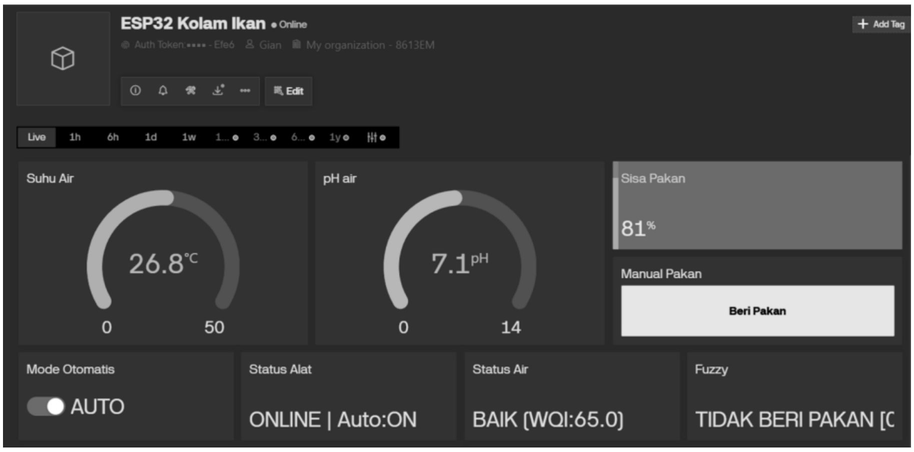

Figure 8. Web Dashboard Testing

Figure 8 shows that the web dashboard displayed the water temperature, pH value, remaining feed level, device status, and automatic operating mode. The recorded temperature of 26.8 °C and pH value of 7.1 were within the suitable region defined by the fuzzy model. However, the OFF indication represents the feeding status at the time of observation, which is determined not only by water-quality suitability but also by the predefined feeding schedule and other operating conditions. This distinction prevents the actuator status from being interpreted directly as the fuzzy decision alone.

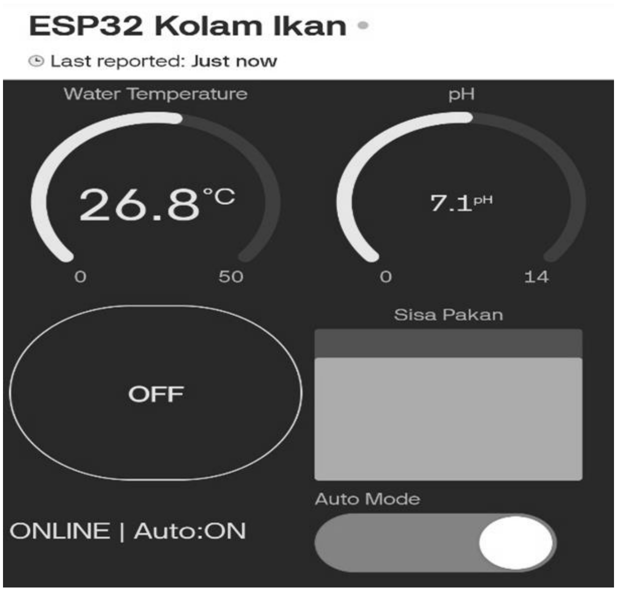

Figure 9. Mobile Dashboard Testing

The mobile dashboard presented the same categories of monitoring and operational information as the web interface, including temperature, pH, feed availability, device connectivity, automatic mode, and feeding status. This result indicates that the information transmitted by the ESP32 could be accessed through different user interfaces without changing the principal monitoring functions. The manual feeding control also provided an alternative command when user intervention was required. Nevertheless, remote monitoring and control remained dependent on network availability, whereas sensor acquisition and fuzzy logic processing continued to operate locally on the ESP32.

3.4 Descriptive Data

Descriptive statistical analysis was conducted to summarize the characteristics of the field data recorded during the monitoring period. The analysis included the minimum, maximum, average, standard deviation, and range of water temperature and pH measurements. These indicators were used to identify the central tendency and variability of each

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parameter before the data were evaluated through the fuzzy logic model. The statistical summary of the sensor measurements is presented in Table 6.

Table 6. Statistical Summary of Sensor Measurements

Sensor	Minimum	Maximum	Average	Standard Deviation	Range
Temperature (°C)	20.6	28.81	24.99	2.05	8.21
pH	6.98	8.43	7.76	0.44	1.45

Table 6 shows that the recorded water temperature ranged from 20.60 to 28.81 °C, with an average value of 24.99 °C. The standard deviation of 2.05 °C and the range of 8.21 °C indicate moderate variation during the observation period. Based on the membership ranges defined in the fuzzy model, the temperature data covered Poor, Fair, Good, and Optimal conditions. The recorded values were therefore not concentrated within a single category and provided sufficiently varied input conditions for evaluating changes in fuzzy membership degrees.

The pH measurements ranged from 6.98 to 8.43, with an average value of 7.76. Compared with temperature, pH showed a lower standard deviation of 0.44 and a narrower range of 1.45, indicating more stable conditions throughout the monitoring period. Most pH values were distributed within the Optimal and Good regions, while several measurements approached the Fair category on the alkaline side. This pattern suggests that pH generally remained within a suitable region, although variations near the category boundaries could still influence the membership degrees and the strength of the activated fuzzy rules.

Overall, temperature exhibited greater variability than pH and was therefore more likely to contribute to changes in the fuzzy feeding decision during the observation period. The combination of relatively stable pH values and more dynamic temperature measurements provided a useful range of actual pond conditions for examining how the fuzzy logic model responded to different input combinations. These descriptive results also formed the basis for the subsequent validation of the rule outputs and the analysis of the system response over time.

3.5 Fuzzy Logic Decision Validation

Fuzzy logic decision validation was conducted to examine the consistency between the feeding decisions generated by the ESP32 program and the rule base defined in Table 2. Five measured combinations of water temperature and pH were selected to represent different input categories and decision conditions. Each value was classified according to the fuzzy category ranges presented in Table 1, after which the expected decision was determined from the corresponding combination of temperature and pH categories. The expected outputs were then compared with the program decisions, as presented in Table 7.

Table 7. Fuzzy Rule Base Validation

Test	Temperature (°C)	pH	Temperature Category	pH Category	Expected Decision	Program Decision
1	22.96	6.78	Fair	Optimal	Feed ON	Feed ON
2	26.85	9.15	Optimal	Poor	Feed OFF	Feed OFF
3	24.85	3.61	Good	Very Poor	Feed OFF	Feed OFF
4	20.84	10.36	Poor	Very Poor	Feed OFF	Feed OFF
5	30.93	7.41	Optimal	Optimal	Feed ON	Feed ON

Table 7 shows that the program produced decisions consistent with the expected outputs for all five combinations. Tests 1 and 5 generated Feed ON because both temperature and pH were classified as Fair or better. Tests 2 and 3 generated Feed OFF because pH was classified as Poor or Very Poor despite acceptable temperature conditions. Test 4 also generated Feed OFF because temperature was classified as Poor and pH as Very Poor. These results confirm that a suitable condition in one parameter cannot compensate for an unsuitable condition in the other, in accordance with the decision structure established in the fuzzy rule base.

All five program outputs matched the expected decisions, resulting in 100% decision conformity for the selected validation cases. This finding indicates that the implemented logic consistently translated the evaluated temperature and pH combinations into the intended Feed ON and Feed OFF outputs. However, the validation was limited to five representative combinations and did not cover all 25 possible category pairs. Therefore, the results demonstrate computational consistency for the tested cases but do not directly establish the biological effectiveness of the feeding strategy, including fish growth, feed conversion efficiency, or behavioral response.

3.6 System Analysis

System analysis was conducted to examine the temporal behavior of water temperature and pH and their relationship with the fuzzy-based feeding process during field monitoring. The recorded data were analyzed using hourly and daily aggregation to reveal the main trends, the variability of each parameter, and the feeding decisions generated at the scheduled evaluation times.

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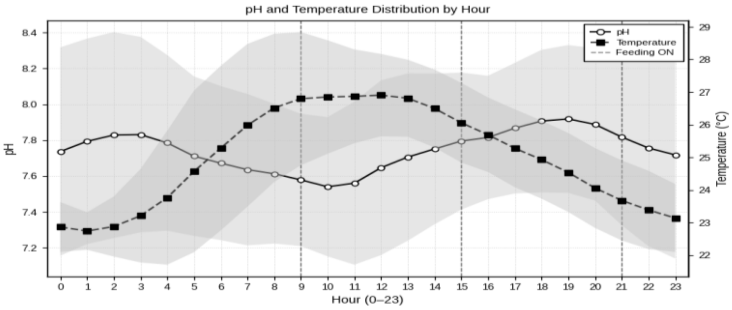

Figure 10. Hourly pH and Temperature Variation

Figure 10 presents the hourly mean pH and water temperature together with their standard deviations. The mean pH remained within a relatively narrow range of approximately 7.54–7.92. It decreased gradually from the early morning until around 10:00, then increased toward the evening before declining slightly at night. In comparison, water temperature showed a clearer daily pattern, increasing from approximately 22.8 °C at midnight to around 27.0 °C near midday and subsequently decreasing during the afternoon and evening. The shaded regions indicate the variability around the hourly means and show that temperature experienced wider fluctuations than pH. The vertical dashed lines at 09:00, 15:00, and 21:00 indicate the scheduled times at which the system evaluated the paired temperature and pH measurements before determining feeding eligibility.

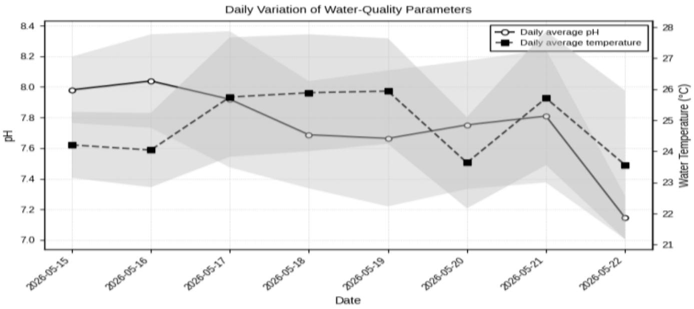

Figure 11. Daily pH and Temperature Variation

Figure 11 shows the daily means and standard deviations of both water-quality parameters during the observation period. Daily mean pH varied from approximately 7.15 to 8.03. Most values were located within the Optimal and Good categories, although the highest values entered the Fair category on the alkaline side. Daily mean temperature ranged from approximately 23.5 to 26.0 °C and was mainly distributed within the Good and Optimal categories. Temperature displayed more visible changes between observation dates, whereas pH remained comparatively stable until a more pronounced decrease on the final day. The standard deviation regions show that individual measurements still varied around the daily means. Therefore, daily averages alone cannot fully represent the actual conditions at a specific feeding time, which supports the need for continuous sensor measurements during system operation.

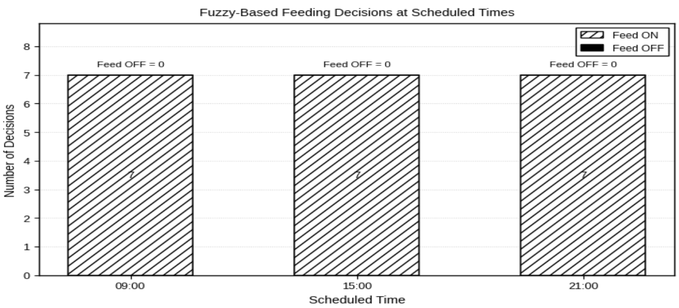

Figure 12. Scheduled Fuzzy Feeding Decisions

Figure 12 summarizes the feeding decisions generated at the scheduled times of 09:00, 15:00, and 21:00. Seven Feed ON decisions were recorded at each scheduled time, yielding 21 Feed ON decisions and no Feed OFF decisions. This outcome indicates that all paired temperature and pH measurements at the scheduled evaluations satisfied the minimum rule-base requirements. The same result occurred consistently at all three feeding times throughout the seven-day monitoring period.

The absence of Feed OFF during field monitoring does not mean that the system was unable to reject unsuitable conditions. Table 7 shows that the program produced Feed OFF when either temperature or pH was classified as Poor or Very Poor. Taken together, the hourly patterns, daily variations, and scheduled decisions demonstrate consistency between monitored conditions and the implemented fuzzy decision rules. However, unsuitable conditions did not occur

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at the scheduled times during the observation period. Consequently, these results confirm the operational consistency of the decision process but do not establish its effect on fish growth, feed conversion efficiency, or feeding behavior.

3.7 Discussion

The experimental results indicate that the developed prototype integrated water-quality monitoring, feed-level observation, fuzzy logic-based decision-making, automatic feed dispensing, and Internet of Things communication within one system. The temperature, pH, and ultrasonic sensors achieved measurement accuracies of 95.52%, 95.87%, and 95.97%, respectively. These values indicate measurement performance sufficient for the intended functions within the tested ranges. The ESP32 processed data locally and transmitted monitoring information to web and mobile dashboards, enabling real-time observation of pond conditions, feed availability, device status, and feeding activity during operation.

The fuzzy logic validation showed that all five selected input combinations produced program decisions consistent with the expected outputs. Feed OFF was generated whenever temperature or pH was classified as Poor or Very Poor, even when the other parameter remained acceptable. Feed ON was permitted only when both parameters were classified as Fair, Good, or Optimal. This structure prevents an unsuitable condition in one parameter from being offset by a suitable condition in the other. The five cases achieved 100% decision conformity, although this result applies only to the evaluated combinations and does not represent all 25 category pairs available in the complete rule base.

Field monitoring showed comparatively stable pH, while water temperature exhibited greater hourly and daily variation. All 21 evaluations conducted at 09:00, 15:00, and 21:00 resulted in Feed ON because the paired measurements satisfied the minimum rule-base requirements. The schedule therefore served as an evaluation time rather than an independent actuator trigger. No naturally occurring Feed OFF condition was recorded, but the validation cases confirmed that the program rejected feeding when one input entered the Poor or Very Poor category. These findings demonstrate operational consistency between the monitored conditions and implemented rules under the observed field conditions.

Compared with the systems developed by Chen et al. [4] and Shete et al. [5], which emphasized continuous monitoring and data transmission, the proposed system links sensor measurements directly to feeding eligibility. Nagothu et al. [6] applied fuzzy logic to broader water-quality management using different control variables, while Prafanto et al. [7] focused on water-quality regulation in tilapia cultivation. This study instead applies a compact, interpretable rule structure to produce binary feeding decisions for catfish ponds. The model operates on the ESP32 without requiring an external platform for decision processing, which supports deployment in small-scale cultivation settings.

The web and mobile dashboards extended the system beyond passive presentation. Previous dashboard-oriented studies [8], [9] emphasized remote observation, whereas the interface here displayed sensor measurements together with feed availability, operating status, and feeding activity. The dashboard supported operational supervision while sensing and fuzzy processing continued locally on the microcontroller. Remote monitoring remained network-dependent, but communication loss did not interrupt local sensing and decision functions, preserving the core control process.

Several limitations must be considered. The fuzzy model used only temperature and pH and excluded dissolved oxygen, ammonia, turbidity, and other variables that may affect fish condition and feeding response. The output was limited to Feed ON and Feed OFF and did not regulate feed quantity according to biomass, growth stage, or feeding intensity. Field observation lasted seven days, produced no naturally occurring Feed OFF condition at scheduled times, and did not evaluate fish growth, feed conversion ratio, uneaten feed, or behavioral response. Longer trials are also needed to assess whether decision consistency is maintained under seasonal changes, sensor drift, and changing fish biomass levels. The results therefore confirm computational and operational consistency for the tested implementation, while further field evaluation is required to determine biological and economic effectiveness.

4. CONCLUSION

This study developed an Internet of Things-based monitoring and automatic feeding system that links real-time water temperature and pH measurements with fuzzy logic-based feeding decisions for catfish ponds. The implemented prototype combined an ESP32, temperature, pH, and ultrasonic sensors, a servo actuator, and web and mobile dashboards within a single monitoring and control platform. Sensor testing produced measurement accuracies of 95.52% for temperature, 95.87% for pH, and 95.97% for ultrasonic distance measurement, indicating adequate performance within the tested ranges. Fuzzy decision validation showed that all five selected cases matched the expected rule-base outputs, while all 21 scheduled field evaluations resulted in Feed ON because the paired temperature and pH values were classified as Fair, Good, or Optimal. These results demonstrate consistent computational and operational behavior, with feeding eligibility determined by current water conditions rather than by schedule alone. The main contribution lies in a compact and interpretable decision mechanism executed locally on the ESP32 while maintaining remote supervision through the dashboards. However, the model was limited to temperature and pH, produced only binary feeding outputs, and was evaluated over seven days without measuring fish growth, feed conversion ratio, or uneaten feed. Future work should include additional water-quality parameters, adaptive feed-quantity control, longer field trials, and biological and economic performance assessment. This expansion may improve applicability across diverse small-scale aquaculture conditions. It may also support more responsive and sustainable feeding management.

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