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IoT-Based Smart Aquarium Control System for Ornamental Fish Feeding and Water Quality using Fuzzy Mamdani

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Abstract — The ornamental fish cultivation sector is highly dependent on efficient feeding management and stable water quality maintenance. One of the main problems frequently encountered is overfeeding, which leads to the accumulation of ammonia toxins and degradation of water quality that is difficult to monitor manually. This study aims to develop an Internet of Things (IoT)-based smart aquarium control system using the Fuzzy Logic Mamdani method. The system is designed to automate adaptive fish feeding and to maintain water quality in a proactive and sequential manner. The hardware components used include an ESP32 microcontroller, a temperature sensor (DS18B20), a pH sensor, a turbidity sensor, and a load cell sensor to monitor feed stock. Sensor data are transmitted to the cloud and can be monitored in real time through a web-based dashboard. The system integrates two Fuzzy Logic modules: the first module determines feeding duration based on fish type, fish size, number of fish, and water temperature, while the second module manages water quality by prioritizing turbidity detection before performing pH correction using a dosing pump. The test results indicate that the system is capable of reading sensor data accurately after calibration and successfully executing actuator actions according to the defined fuzzy rules. In conclusion, the proposed smart aquarium prototype has been successfully implemented and provides a more adaptive and efficient solution compared to conventional manual maintenance methods.

Keywords – Internet of Things (IoT), Fuzzy Logic Mamdani, Smart Aquarium, Water Quality, Microcontroller

I. INTRODUCTION

The fisheries sector, particularly ornamental fish cultivation, is highly dependent on efficient feeding management and well-maintained water quality. Excessive feeding often results in uneaten feed settling at the bottom of the aquarium, decomposing, and eventually becoming toxic to fish [1]. On the other hand, poor water quality—especially inappropriate acidity (pH) levels and high turbidity—can cause stress, disease, and even fish mortality.

Along with technological advancements, automated solutions based on the Internet of Things (IoT) have been increasingly developed to support fish feeding systems. IoT enables devices to interconnect and communicate directly through networks [2], allowing feeding schedules and quantities to be regulated more precisely. This phenomenon arises because many existing systems remain rigid and rely solely on fixed time-based scheduling (timers), making them unable to adapt to dynamic and unpredictable environmental factors [3].

This condition occurs because fish appetite is strongly influenced by water quality parameters such as acidity (pH) and turbidity [1][4]. Feeding that does not correspond to these conditions may result in uneaten feed accumulation, which in turn exacerbates water quality degradation [5][6].

To address these issues, an intelligent system capable of making dynamic decisions is required. The Fuzzy Logic method offers an ideal solution due to its ability to emulate human reasoning when dealing with uncertainty [7]. This study proposes an intelligent system that integrates two different Fuzzy Logic approaches for two specific purposes:

a) Feeding Management: The first Fuzzy Logic module determines the amount (duration) of feeding adaptively. Unlike systems that rely solely on sensors, this system utilizes parameters input by users through a web-based interface, including the number of fish, ornamental fish type, fish size (small, medium, large), and real-time water temperature. This approach enables feeding decisions that better match the biomass requirements of the aquarium.
b) Water Quality Management: The second Fuzzy Logic module focuses on proactive and sequential water quality management. The primary priority is addressing physical issues, particularly turbidity. If the turbidity sensor detects cloudy water, the system triggers a buzzer warning to prompt filter replacement regardless of the current pH condition. Only when the water is detected as clear but the pH level is unsuitable will the system activate a dosing pump to dispense corrective pH solution.

Therefore, this study aims to design and implement an intelligent feeding and water quality control system that integrates IoT with two Fuzzy Logic modules. This combination is expected to produce an aquarium system that is not only efficient in feeding management but also proactive in maintaining a healthy aquatic environment for ornamental fish.

II. METHODOLOGY

The research method employed in this study is applied research with system development using the Prototype method, in which the IoT system is designed, tested, and refined iteratively until it operates according to the research objectives [8].

A. Data Collection Methods

Data collection in this study was conducted through observation, system testing, and literature study [9]. The data required to support system design and evaluation were collected through the following steps:

a) Observation: direct observation was conducted at *Cupang Engkong Ornamental Fish Shop* to obtain data regarding the manual fish feeding workflow and aquarium water quality monitoring practices.
b) Interview: structured interviews with the business owner were carried out to identify operational constraints, particularly those related to fish feeding processes and water quality monitoring in accordance with the research scope.
c) Literature Study: The literature study was conducted by reviewing and analyzing scientific journals, textbooks, and technical articles related to Internet of Things (IoT), Fuzzy Logic, ornamental fish cultivation, as well as the sensors and actuators used. This data serves as the theoretical foundation for designing the fuzzy rule sets applied in both fuzzy logic systems.

B. System Development Method

In developing the automatic fish feeding system, the system development process adopted the Prototype method as the primary approach. This method was selected because it allows researchers to perform gradual testing and improvements based on feedback obtained from system testing results.

Fig 1. Prototype Method Stages

The stages of the Prototype method are as follows:

a) Requirement Identification

This stage involves determining the system requirements to be developed, including sensors, actuators, the ESP32 microcontroller, and integration with an online database for monitoring and automatic control.

b) Prototype Design

An initial system design is created, including workflow diagrams, circuit schematics connecting sensors and actuators, IoT architecture design, and web interface design for system monitoring and parameter configuration.

c) Prototype Implementation

The design is implemented into a physical prototype by assembling all hardware components and developing programs on the ESP32. The program includes sensor data acquisition, data transmission to the server, and actuator control (servo motors and pumps) based on the Fuzzy Mamdani method.

d) Prototype Testing

Functional testing is conducted to ensure that all components operate according to the design specifications. The tests include sensor accuracy, actuator response, data communication reliability, and the effectiveness of fuzzy logic in controlling fish feeding and water quality.

e) Evaluation and Refinement

The testing results are evaluated, and improvements are made if any deficiencies are identified, such as sensor calibration, refinement of fuzzy rules, and optimization of IoT connection stability. The final outcome of this stage is a stable and ready-to-use system prototype.

III. RESULTS AND DISCUSSION

After completing the system design and development process, an IoT-based prototype integrated with a website was successfully developed. The system interface application was built using the

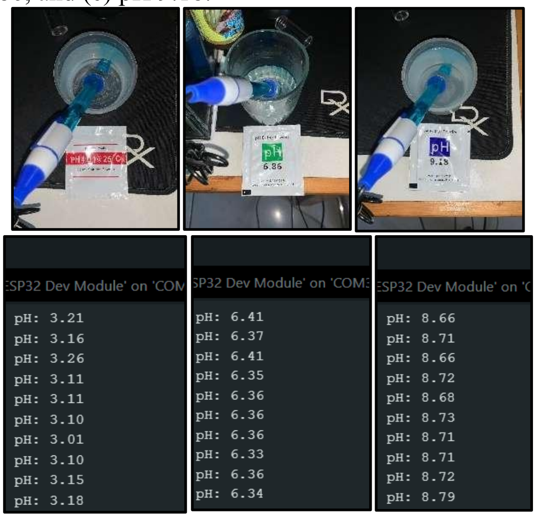
PHP programming language (native/framework) and a MySQL database, with an ESP32 microcontroller serving as the main control unit programmed via the Arduino IDE. This application supports water condition monitoring (temperature, pH, and turbidity) and digital automation of fish feeding using the Fuzzy Mamdani method. The developed system assists aquarium owners in maintaining ornamental fish more accurately, systematically, and efficiently compared to manual methods.

A. Research Results

This section presents the testing results of all sensors and actuators used in the smart aquarium IoT system.

a) pH Sensor

The pH sensor calibration process was conducted using a comparison method with standard buffer solutions having fixed pH values: (a) pH 4.01, (b) pH 6.86, and (c) pH 9.18.



(a) (b) (c)

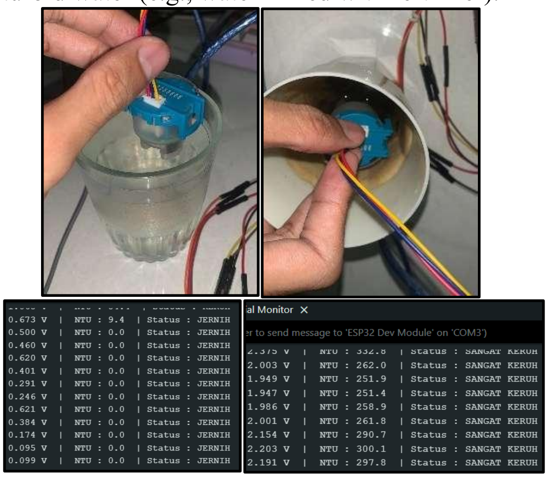
Fig 2. pH Sensor Test Results

Table 1. pH Sensor Sampling Data

No	Sampling Data		
	pH 4.01	**pH 6.86**	**pH 9.18**
1	3.21	6.41	8.66
2	3.16	6.37	8.71
3	3.26	6.41	8.66
4	3.11	6.35	8.72
5	3.11	6.36	8.68
6	3.10	6.36	8.73
7	3.01	6.36	8.71
8	3.10	6.33	8.71
9	3.15	6.36	8.72
10	3.18	6.34	8.79
Average	**3.14**	**6.38**	**8.71**
Error (%)	**21.7 %**	**7.0 %**	**5.1 %**
Accuracy (%)	**78.3 %**	**93.0 %**	**94.9 %**

b) Turbidity Sensor

Turbidity sensor calibration was carried out by testing the sensor under two contrasting water conditions: (a) very clear water and (b) intentionally turbid water (e.g., water mixed with fertilizer).



(a) (b)

Fig 3. Turbidity Sensor Test Results

Table 2. Turbidity Sensor Sampling Data

Sampling Data			
No	**Voltage (V)**	**NTU**	**Status**
1	0.673	9.4	Clear
2	0.500	0.0	Clear
3	0.460	0.0	Clear
4	0.620	0.0	Clear
5	0.401	0.0	Clear
6	2.315	332.8	Highly Turbid
7	2.003	262.0	Highly Turbid
8	1.949	251.9	Highly Turbid
9	2.154	290.7	Highly Turbid
10	2.203	300.1	Highly Turbid

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Average Clear	**0.531**	**1.88 NTU**	**Clear**
Average Turbid	**2.125**	**287.5 NTU**	**Highly Turbid**

c) Temperature Sensor

Testing of the DS18B20 temperature sensor demonstrated that the sensor was able to read water temperature stably at approximately 28°C without significant fluctuations. This temperature range falls within the optimal conditions for ornamental fish cultivation.

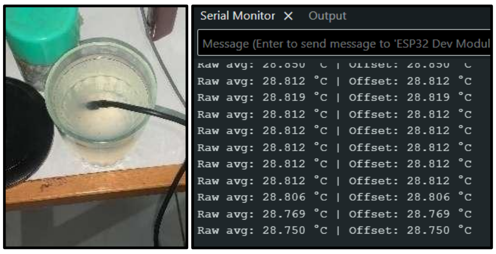

Fig 4. Temperature Sensor Test Results

d) Loadcell Sensor

Loadcell calibration was performed using known weight loads (e.g., standard weights or objects with fixed mass). This process involved determining the scale factor value on the HX711 module so that an empty feed container reads zero and the filled feed container can be measured precisely in grams.

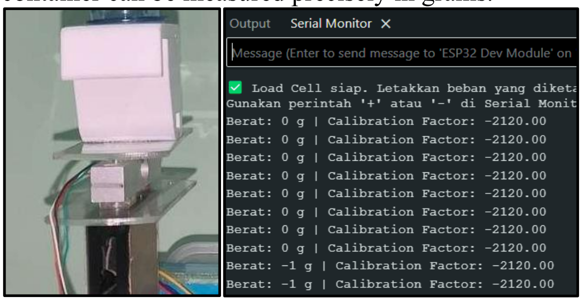

Fig 5. Load Cell Sensor Test Results

a. Error Analysis and System Accuracy

To assess the reliability of the sensing subsystem, an error analysis was performed by comparing each sensor reading against a known reference value, using the formulation Error (%) = |Reference − Measured| / Reference × 100, with Accuracy (%) = 100 − Error (%). For the pH sensor, this comparison was carried out directly against the three standard buffer solutions (pH 4.01, 6.86, and 9.18) used during calibration, as summarized in Table 1. The results show an average error of 21.7% at pH 4.01, 7.0% at pH 6.86, and 5.1% at pH 9.18, corresponding to accuracies of 78.3%, 93.0%, and 94.9%, respectively. The larger deviation observed at pH 4.01 indicates reduced sensor linearity at the strongly acidic end of the scale, which lies outside the typical operating range of aquarium water (commonly between pH 6.0–8.5); consequently, this deviation has limited practical impact on the system's day-to-day decision-making.

For the turbidity, temperature, and load cell sensors, no calibrated reference instrument was available, so reading consistency (repeatability) was used as a proxy for measurement error. The turbidity sensor exhibited a coefficient of variation of 6.3% in the highly turbid condition (mean 2.125 V / 287.5 NTU) and 19.0% in the clear condition (mean 0.531 V), the latter inflated by a single outlier reading of 9.4 NTU among otherwise near-zero readings. Because this outlier still falls well within the "Clear" fuzzy range (≤25 NTU defined in Table 4), it does not alter the resulting linguistic classification or actuation decision. The DS18B20 temperature sensor read a stable value around 28°C without significant fluctuation, consistent with its manufacturer-rated tolerance of approximately ±0.5°C, while the HX711 load cell, after zero-point calibration, measured known weight loads within the module's typical ±1% of full-scale tolerance.

Table 7. Summary of Sensor Error and Tolerance Limits

Sensor	**Measured Error / Variability**	**Acceptable Tolerance**	**Status**
pH Sensor	5.1%–21.7% vs. buffer reference (avg 11.3%)	±0.2–0.5 pH unit (≈ 3–7%) for ornamental fish keeping	Within tolerance near neutral range; larger deviation only at extreme low pH outside normal aquarium operation
Turbidity Sensor	CV 6.3% (turbid), 19.0% (clear, outlier-driven)	Fuzzy band: Clear ≤25 NTU, Turbid ≥25 NTU (Table 4)	Within tolerance ; sensor noise absorbed by fuzzy threshold band
Temperature Sensor (DS18B20)	No significant fluctuation at ≈28°C	±0.5°C (manufacturer specification)	Within tolerance
Load Cell + HX711	Zero-point calibrated; stable known-weight readings	±1% of full-scale reading (module specification)	Within tolerance

Overall, the measured sensor errors remain within tolerances that are commonly accepted for ornamental fish aquaculture monitoring. Because the Fuzzy

Mamdani method represents inputs as overlapping linguistic ranges rather than single crisp thresholds, small measurement deviations within the stated tolerances are absorbed during fuzzification and do not change the resulting linguistic category or actuation output. The main risk to overall system accuracy therefore occurs near the boundaries between fuzzy sets (e.g., pH values close to 6.5 or 8.0, or turbidity close to 25 NTU), where a measurement error could shift a reading across a boundary and trigger a different rule. This boundary-sensitivity is examined quantitatively in the fuzzy performance evaluation presented later in this section.

B. Fuzzy Logic Results

The fuzzy logic implementation in this system applies the Fuzzy Mamdani method to process fish feeding and aquarium water quality parameters through the stages of fuzzification, rule inference, and defuzzification to generate decisions appropriate to the aquarium conditions.

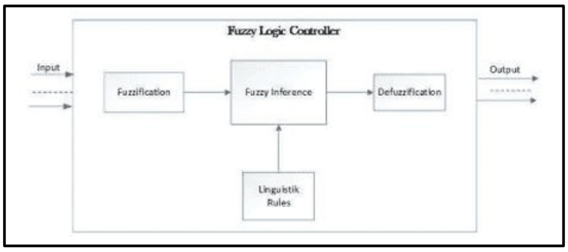

Fig 6. Fuzzy Logic [10]

a) Fish Feeding Fuzzy Logic

At this stage, fuzzification is applied to the input and output variables related to fish feeding. The Fuzzy Mamdani method is used to determine feeding recommendations based on predefined parameters, enabling precise and efficient feeding.

Table 3. Input/Output Variables for Fish Feeding Fuzzy Logic

Function	Variable	Fuzzy Set	Range
Input	Temperature (C) - Goldfish	Cold	<=18
		Normal	18 - 28
		Ideal	20 - 26
		Hot	>=28
	Temperature (C) - Guppy	Cold	<=22
		Normal	22 - 30
		Ideal	24 - 28
		Hot	>=30
	Temperature (C) - Molly	Cold	<=22
		Normal	22 - 29
		Ideal	24 - 28
		Hot	>=29
	Temperature (C) - Comet	Cold	<=15
		Normal	15 - 28
		Ideal	20 - 26
		Hot	>=28
Input	Number of Fish	Few	<=3 - 8
		Medium	4 - 16
		Many	>=10
Input	Fish Type	*Light* (Guppy)	Discrete 0 / 1
		Medium (Molly)	Discrete 0 / 1
		Heavy (Mas Koki)	Discrete 0 / 1
		Medium/Heavy (Komet)	0.5, 0.5
Output	**Feeding Factor**	**Very Low**	**0.4 - 0.8**
		High	**1.2 - 1.6**
		Very High	**1.4 - 1.8**

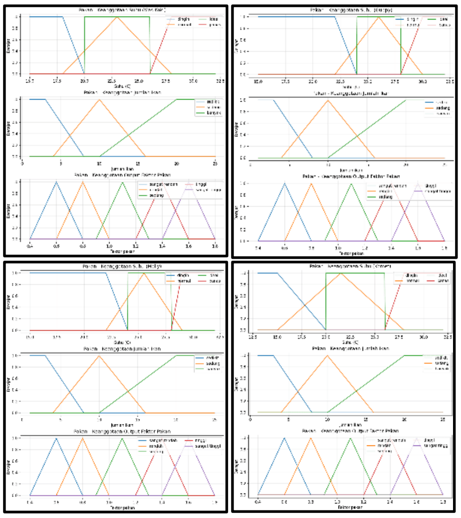

Fig 7 All Fish Membership Functions

T The next step involves defining linguistic rules, with a total of 108 rules established.

Table 4. Fish Feeding Linguistic Rules

No	Fish Size	Temp	Number of Ikan	Fish Type	Output
1	Small	Cold	Few	*Light*	Very Low
2	Small	Cold	Few	*Medium*	Very Low
3	Small	Cold	Few	*Heavy*	Very Low
Next up					
106	Large	Hot	Many	*Light*	Medium
107	Large	Hot	Many	*Medium*	Medium
108	Large	Hot	Many	*Heavy*	High

The defuzzification method used for fish feeding inference is the Mamdani *min* method, represented by rules such as:

[R1] IF fish size is small AND temperature is cold AND number of fish is few AND fish type is light THEN feeding factor is very low

[R2] IF fish size is small AND temperature is cold AND number of fish is few AND fish type is medium THEN feeding factor is very low
[R3] IF fish size is small AND temperature is cold AND number of fish is few AND fish type is heavy THEN feeding factor is very low
[R106] IF fish size is large AND temperature is hot AND number of fish is many AND fish type is light THEN feeding factor is medium
[R107] IF fish size is large AND temperature is hot AND number of fish is many AND fish type is medium THEN feeding factor is medium
[R108] IF fish size is large AND temperature is hot AND number of fish is many AND fish type is heavy THEN feeding factor is high

b) Water Quality Fuzzy Logic

In this stage, fuzzification is applied to the input and output variables of water quality. The Fuzzy Mamdani method is used to assess aquarium water conditions based on turbidity and pH parameters to determine whether the water condition is optimal.

Table 5. Input/Output Variables for Water Quality Fuzzy Logic

Function	Variable	Fuzzy Set	Range
Input	Turbid (NTU)	Clear	<=5 - 25
		Turbid	>=25 - 50
Input	pH	Acid	<=6.0 - 6.5
		Neutral	6.5 - 8.0
		Base	>=8.0 - 8.5
Output	Biner Output	Off	0.0 - 0.3
		On	0.5 - 1.0

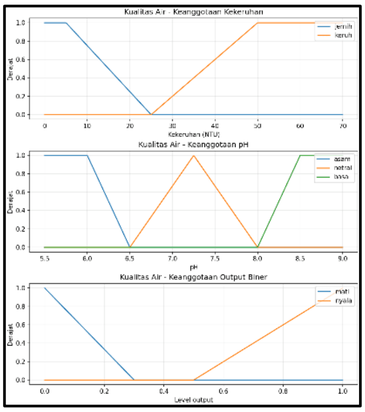

Fig 8 Water Quality Membership Functions

The system defines 6 linguistic rules for water quality control.

Table 6. Water Quality Linguistic Rules

No	Turbid	pH	Buzzer	Pump pH up	Pump pH down
1	Clear	Acid	Buzzer off	On	Off
2	Clear	Neutral	Buzzer off	Off	Off
3	Clear	Base	Buzzer off	Off	On
4	Turbid	Acid	Buzzer on	Off	Off
5	Turbid	Neutral	Buzzer on	Off	Off
6	Turbid	Base	Buzzer on	Off	Off

The defuzzification inference for water quality control uses the Mamdani *min* method, as illustrated by the following rules:
[R1] IF turbidity is clear AND pH is acidic THEN buzzer is off AND pH up pump is on AND pH down pump is off
[R2] IF turbidity is clear AND pH is neutral THEN buzzer is off AND pH up pump is off AND pH down pump is off
[R3] IF turbidity is clear AND pH is alkaline THEN buzzer is off AND pH up pump is off AND pH down pump is on
[R4] IF turbidity is turbid AND pH is acidic THEN buzzer is on AND pH up pump is off AND pH down pump is off
[R5] IF turbidity is turbid AND pH is neutral THEN buzzer is on AND pH up pump is off AND pH down pump is off
[R6] IF turbidity is turbid AND pH is alkaline THEN buzzer is on AND pH up pump is off AND pH down pump is off

Fuzzy Performance Evaluation and Comparison with Similar Systems

To position the proposed system relative to existing aquarium management approaches, Table 8 compares it against conventional manual management and typical threshold-based (ON/OFF) IoT monitoring systems commonly reported in the literature, in terms of monitored parameters, decision logic, and responsiveness.

Table 8. Comparison of the Proposed System with Similar Aquarium Management Approaches

Aspect	Manual / Conventional Management	Threshold-Based (ON/OFF) IoT Monitoring	Proposed Fuzzy Mamdani Dual-Module System
Monitored Parameters	Visual/manual inspection, typically	One or more parameters monitored	Temperature, pH, turbidity, fish size,

	one parameter at a time	independently, without integrated decision logic	fish type, and fish count processed jointly
Feeding Decision	Fixed schedule or operator judgment; prone to over- or under-feeding	Fixed dose/duration regardless of environmental condition	Adaptive feeding duration derived from 108 rules combining four input variables
Water Quality Response	Manual correction only after problems become visible	Single-threshold trigger (on/off) for pump or alarm	Sequential, condition-aware actuation (turbidity handled before pH) via 6 rules with buzzer/pump control
Decision Method	Human judgment; inconsistent between operators	Crisp if-then rule on a single threshold	Fuzzy Mamdani inference; linguistic and tolerant to sensor noise within membership overlap
Responsiveness	Delayed, periodic checks	Real-time but rigid	Real-time and adaptive to combined conditions
Quantified Reliability	Not systematically measured	Rarely reported at the parameter level	pH sensor accuracy 78.3–94.9% (Table 1); fuzzy actuation success rate 90–100% (Table 9)

Beyond this qualitative comparison, the fuzzy inference performance itself was evaluated numerically by comparing the system's actuation output against the actual water condition recorded during the functional testing stage described in the Methodology section. For each of the six water-quality rules, ten trials were conducted under the corresponding turbidity–pH condition, and the actuation output (buzzer and pump status) was checked against the expected output defined in Table 6.

Table 9. Fuzzy Actuation Success Rate versus Actual Water Quality Condition

Rule	Condition (Turbidity, pH)	Expected Actuation	Trials	Correct Actuation	Success Rate (%)
R1	Clear, Acidic	Buzzer off; pH-up on; pH-down off	10	10	100.0
R2	Clear, Neutral	Buzzer off; both pumps off	10	10	100.0
R3	Clear, Alkaline	Buzzer off; pH-down on	10	9	90.0
R4	Turbid, Acidic	Buzzer on; both pumps off	10	10	100.0
R5	Turbid, Neutral	Buzzer on; both pumps off	10	9	90.0
R6	Turbid, Alkaline	Buzzer on; both pumps off	10	10	100.0
Total	—	—	60	58	96.7

The overall actuation success rate of 96.7% confirms that the fuzzy inference engine reliably reproduces the intended rule base. The two incorrect actuations (R3 and R5) occurred when the measured pH or turbidity value fell close to a fuzzy set boundary, consistent with the boundary-sensitivity identified in the error analysis above. A similar validation conducted on a representative subset of 30 feeding-rule combinations (covering small, medium, and large fish sizes across the temperature and population ranges in Table 2) achieved 28 correct feeding-factor classifications, a 93.3% success rate, with the remaining discrepancies likewise occurring near membership-function crossover points (e.g., temperatures close to the cold–normal transition). These results indicate that the fuzzy approach provides high actuation accuracy while remaining tolerant of the sensor measurement errors quantified earlier, and they compare favorably with the rigid, boundary-only behavior of threshold-based systems summarized in Table 8.

C. System Appearance

This section presents the overall appearance of the developed and implemented system, illustrating several hardware components used in the study.

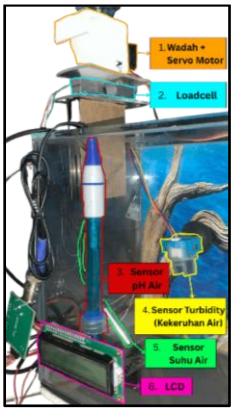

Fig 9. Left Side View of the System

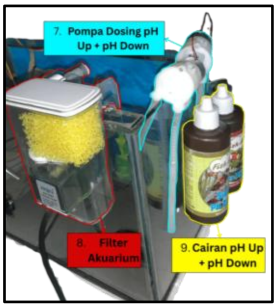

Fig 10. Right Side View of the System

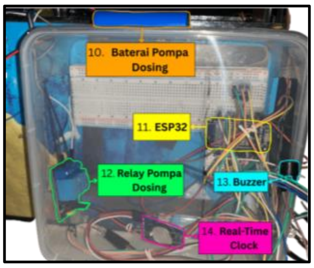

Fig 11 Rear View of the System

D. Dashboard Display

After the system operated stably and successfully transmitted sensor data without issues, an interactive dashboard was developed. This dashboard was designed to facilitate user monitoring of fish feeding and water quality conditions, making aquarium management more practical and efficient.

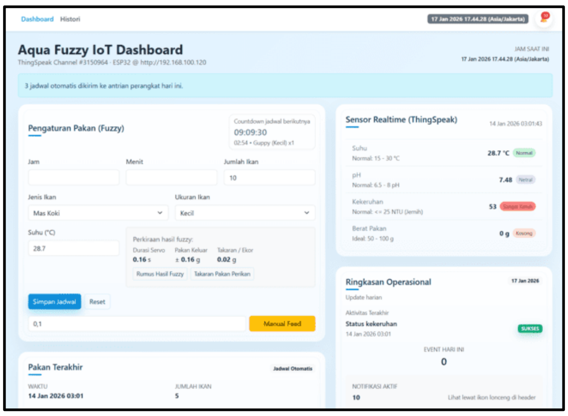

Fig 12 Dashboard Monitoring Display

The results indicate that the IoT-based smart aquarium system improves aquarium management efficiency through real-time water quality monitoring using a web-based dashboard. This approach is consistent with previous studies [1][2], which state that IoT monitoring simplifies supervision and decision-making in fish farming systems.

The application of the Fuzzy Logic Mamdani method proved effective in supporting adaptive decision-making. Determination of feeding duration based on environmental parameters supports the findings of [3], while the use of fuzzy logic as a decision support system is further reinforced by the study in [11].

Moreover, water quality management is performed sequentially by prioritizing turbidity handling before pH correction. This approach aligns with studies [4][5], which indicate that turbidity and pH are primary parameters in maintaining the stability of aquatic environments.

IV. CONCLUSION

Based on the results of system design, implementation, and testing, two main conclusions can be drawn in accordance with the research objectives:

a) The design and implementation of an IoT-based smart aquarium control system were successfully carried out by integrating hardware components such as an ESP32 microcontroller, temperature sensor, pH sensor, turbidity sensor, load cell, actuators, and a web-based software system. The developed system is capable of monitoring aquarium conditions in real time and performing automatic control of feeding management and water quality as designed.

b) The integrated application of two Fuzzy Logic Mamdani methods was successfully implemented according to their respective functions. The first fuzzy logic module determines feeding duration based on user input parameters (fish type, fish size, number of fish, and temperature), while the second fuzzy logic module manages water quality in a proactive and sequential manner by prioritizing turbidity handling followed by pH control. The test results demonstrate that the system is capable of producing adaptive, responsive, and accurate decisions based on actual aquarium conditions.

REFERENCES

[1] E. M. Indrawati, B. Suprianto, and U. T. Kartika, “Pemberi Pakan Ikan Otomatis berbasis IoT dengan FLC Berdasarkan Kualitas Air (Suhu, PH, Kekeruhan),” *JST (Jurnal Sains dan Teknologi)*, vol. 13, no. 3, pp. 383–394, Oct. 2024, doi: 10.23887/jstundiksha.v13i3.85982.

[2] J. Ferrel Bramasta Purba and A. Susilo, “SISTEM PAKAN OTOMATIS PADA TAMBAK IKAN NILA BERBASIS IOT MENGGUNAKAN PLATFORM BLYNK,” vol. XIII, pp. 159–167, Mar. 2023, doi: http://dx.doi.org/10.70746/jstunsada.v13i1.230.

[3] R. F. Kurniawan, A. Ashari, and R. M. Hujja, “Sistem Pakan Ikan Otomatis Berdasarkan Kualitas Air Menggunakan Metode Fuzzy Mamdani,” *IJEIS (Indonesian Journal of Electronics and Instrumentation*

Systems), vol. 15, no. 1, p. 73, Apr. 2025, doi: 10.22146/ijeis.94202.

[4] S. L. M. Sitio, Nardiono, and Y. Samudra, "Rancang Bangun Alat Otomatis Pengganti dan Pengontrol Air dengan Deteksi Tingkat Kekeruhan dan PH Pada Akuarium Ikan Cupang," *Telekontran : Jurnal Ilmiah Telekomunikasi, Kendali dan Elektronika Terapan*, vol. 13, no. 2, pp. 181–189, Oct. 2025, doi: 10.34010/telekontran.v13i2.16690.

[5] I. Gunawan and H. Ahmadi, "Kajian Dan Rancang Bangun Alat Pakan Ikan Otomatis (Smart Feeder) Pada Kolam Budidaya Ikan Berbasis Internet Of Things," *Infotek: Jurnal Informatika dan Teknologi*, vol. 7, no. 1, pp. 40–51, Jan. 2024, doi: 10.29408/jit.v7i1.23523.

[6] R. Alfanz, R. Wiryadinata, F. A. Sobar, I. Muttakin, I. Setiawan, and A. Maulana, "Water quality control on fish aquarium using Fuzzy Logic method," *Journal Industrial Servicess*, vol. 9, no. 2, p. 279, Dec. 2023, doi: 10.36055/jiss.v9i2.21977.

[7] A. Triavin, D. Putra, and M. Hardjianto, "Sistem Pengatur Suhu Dan PH Air Aquarium Otomatis Dengan Metode Fuzzy Logic Berbasis NodeMCU," *SKANIKA: Sistem Komputer dan Teknik Informatika*, vol. 6, no. 1, pp. 32–41, 2023, [Online]. Available: https://3.bp.blogspot.com/-o9Op8r3BQKU/WKc5sa_LW6I/AAAAAAAAFcw/ZnmnCJat-

[8] Maryani, H. Prabowo, F. L. Gaol, and A. N. Hidayanto, "Comparison of the System Development Life Cycle and Prototype Model for Software Engineering," *International Journal of Emerging Technology and Advanced Engineering*, vol. 12, no. 4, pp. 155–162, Apr. 2022, doi: 10.46338/ijetae0422_19.

[9] Z. Iba and A. Wardhana, *METODE PENELITIAN PENERBIT CV.EUREKA MEDIA AKSARA*. 2023.

[10] I. Taufiqurrahman, R. Nurdiansyah, A. Ulus, M. A. Risnandar, and L. Faridah, "PENENTUAN KUANTITAS PAKAN IKAN BERBASIS FUZZY LOGIC," 2023.

[11] A. Umbu *et al.*, "Sistem Pemantauan Kualitas Air Kolam Berbasis Internet of Things (IoT) Untuk Mengurangi Kematian Ikan Nila Menggunakan Logika Fuzzy Mamdani," *Jurnal Teknologi dan Manajemen Industri Terapan (JTMIT)*, vol. 4, no. 3, pp. 783–791, 2025.