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An IoT-Based Smart Feeding System for Koi Fish Using Mamdani Fuzzy Logic

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Abstract
Koi feeding management requires precision in both feeding timing and feed quantity to maintain fish health and reduce mortality rates. Manual feeding practices are often inconsistent due to human limitations, leading to overfeeding or underfeeding. This study proposes an IoT-based smart feeding system for koi fish that integrates Mamdani fuzzy logic to determine adaptive feeding durations based on feed stock conditions. The system employs a NodeMCU ESP8266 microcontroller, an ultrasonic sensor for feed-level monitoring, a servo motor for feed dispensing, and the Blynk platform for real-time remote monitoring and control over the internet. Mamdani fuzzy inference is utilized to classify feed levels into linguistic variables (low, medium, and high) and generate appropriate feeding actions. Experimental results demonstrate that the proposed system operates reliably, with an average measurement error of 1.59%, indicating high accuracy in feed-level detection. The fuzzy logic controller effectively adjusts feeding duration according to feed availability, enabling consistent and controlled feeding schedules. The proposed system offers a practical and low-cost solution for intelligent koi fish feeding management and can be extended to broader applications in smart aquaculture systems.

Keywords: *Fuzzy Logic, Internet of Things, Koi Fish, Smart Feeding.*

I. INTRODUCTION

Koi fish (*Cyprinus rubrofuscus*) are widely cultivated as ornamental fish for their aesthetic appeal and economic value. However, koi fish are highly sensitive to environmental conditions and feeding patterns, making proper feed management a critical factor for maintaining fish health and minimizing mortality rates (Andrian et al., 2024). Inappropriate feeding practices, such as irregular feeding schedules and excessive feed portions, can negatively affect water quality and fish metabolism, leading to stress and disease outbreaks (Tarihoran et al., 2024) (Kusrini et al., 2015).

In traditional koi fish cultivation, feeding activities are generally performed manually, relying heavily on human presence and consistency. This approach is often inefficient, particularly for breeders with limited time or who manage multiple ponds. Human error, including missed feeding times or inaccurate feed portions, remains a significant challenge in conventional feeding systems (Noor et al., 2012) (Amarudin et al., 2020). Therefore, the development of automated feeding solutions has become an important research topic in smart aquaculture systems.

The rapid advancement of Internet of Things (IoT) technology has enabled the integration of sensors, microcontrollers, and cloud platforms to support real-time monitoring and automation in aquaculture applications (Daru et al., 2024). IoT-based systems have been widely applied for fish

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feeding, water quality monitoring, and environmental control, offering improved efficiency and remote accessibility (Prapti et al., 2022). By leveraging wireless connectivity, IoT platforms enable fish farmers to monitor feeding processes and system conditions via mobile or web-based interfaces.

Several studies have demonstrated the effectiveness of fuzzy logic–based feeding systems in poultry and aquaculture applications(Nagothu et al., 2025). However, research on koi fish feeding systems integrating IoT and adaptive fuzzy logic control remains limited. Moreover, many existing systems lack real-time feedstock monitoring and rely on predefined feeding durations without accounting for feed availability. Despite these advancements, many existing automatic fish-feeding systems rely on fixed schedules or simple threshold-based controls that do not adapt to dynamic feeding conditions. This is the current limitation of the previous models

To address these gaps, this study proposes an IoT-based smart feeding system for koi fish using Mamdani fuzzy logic to regulate feeding duration based on feed stock levels. Compared to previous models that relied on predefined configuration or threshold controls, the proposed model used Fuzzy Mamdani as a controller for dynamic situations. Thus, the proposed model can adapt the environmental changes easily. The Fuzzy Mamdani algorithm was proposed to address the limitations of previous models, introducing intelligent decision-making methods such as fuzzy logic. Fuzzy logic is well-suited for handling uncertainty and linguistic variables, making it effective for modeling feeding behavior that resembles human reasoning(Tang et al., 2014). In particular, the Mamdani fuzzy inference method has been widely adopted in control systems due to its interpretability and robustness (Sutabri et al., 2021). The system integrates a NodeMCU ESP8266 microcontroller, an ultrasonic sensor for feed level detection, a servo motor for feed dispensing, and the Blynk cloud platform for real-time monitoring and control. By combining IoT connectivity with fuzzy logic decision-making, the proposed system aims to provide a reliable, adaptive, and cost-effective solution for intelligent koi fish feeding management.

II. LITERATURE REVIEW

The application of the Internet of Things (IoT) in aquaculture has received increasing attention due to its ability to enhance feeding efficiency, reduce operational costs, and improve fish health management through automation and real-time monitoring (Firmansyah et al., 2026; Nanjar et al., 2024; Susilo & Susanto, 2024). IoT-based feeding systems commonly integrate sensors (Ibrahim et al., 2024; Mase et al., 2025), microcontrollers, cloud platforms, and mobile applications to enable continuous data acquisition and remote control. (Li et al., 2020) reported that IoT-enabled aquaculture systems are effective in reducing feed waste while maintaining optimal growth conditions, whereas (Xu et al., 2026) demonstrated improved feeding consistency when automated feeders are connected to cloud-based platforms. Several studies have implemented smart feeding mechanisms using microcontrollers such as the Arduino and the ESP8266; however, many of these rely on fixed feeding schedules. For example, (Mohamed et al., 2024) proposed an IoT-based automatic fish feeder with mobile monitoring, yet the system lacked adaptive decision-making capabilities. Consequently, existing studies often treat IoT automation and intelligent control as separate approaches. Limited research integrates Mamdani fuzzy logic within a fully IoT-enabled framework that supports adaptive feeding decisions and quantitative accuracy evaluation, particularly for ornamental species such as koi fish.

A. Intelligent Control Techniques for Feeding Automation

To overcome the limitations of static feeding strategies, intelligent control methods have been introduced into aquaculture automation. Artificial intelligence techniques, including fuzzy logic, neural networks, and rule-based systems, have been widely adopted to handle uncertainty and nonlinear relationships in biological systems. Fuzzy logic, in particular, has proven effective in decision-making scenarios where precise mathematical models are difficult to obtain. Mamdani fuzzy inference systems have been extensively applied in control applications due to their intuitive rule-based structure and interpretability. In the context of aquaculture, (Zhou, 2018.) implemented a fuzzy logic controller to regulate feeding rates based on fish behavior and environmental parameters, achieving improved feed utilization efficiency. Likewise, (Pribadi et al., 2020) Applied Mamdani fuzzy logic to determine feeding duration in an automated fish feeder, demonstrating better adaptability compared to conventional threshold-based systems. Despite these advances, most fuzzy logic–based feeding systems operate as standalone solutions without seamless integration into IoT ecosystems. As noted by (Mudholkar et al., 2025), the absence of real-time cloud connectivity limits system scalability, data visualization, and remote management, which are essential features of modern smart aquaculture platforms.

B. Sensor-Based Feed Monitoring and System Accuracy

Accurate feed level detection is a fundamental requirement for reliable automatic feeding systems. Ultrasonic sensors are commonly used for non-contact feed level measurement due to their low cost, ease of integration, and acceptable accuracy. Studies by (Papini et al., 2025) and (Choudhary et al., 2021) reported that ultrasonic sensors provide sufficient precision for monitoring granular feed levels when properly calibrated. However, many IoT-based feeding studies do not quantitatively assess sensor accuracy, raising concerns about long-term reliability and system robustness.

Furthermore, several researchers have highlighted the importance of validating system performance through error analysis and experimental testing. Accurate sensor data are essential for intelligent controllers such as fuzzy logic, as incorrect input values may lead to suboptimal feeding decisions (Belgacem & Chihi, 2025; Singh et al., 2021)

III. RESEARCH METHOD

A. Research Design

Block diagram design is a crucial step in system development, as it provides a clear representation of the overall operating principle and the interactions among system components. Block diagrams make the functional structure and data flow of the entire system easy to understand. Figure 1 illustrates the block diagram of the proposed IoT-based automatic feeding system, which uses a NodeMCU microcontroller and Mamdani fuzzy logic. The system architecture consists of several interconnected components with specific roles.

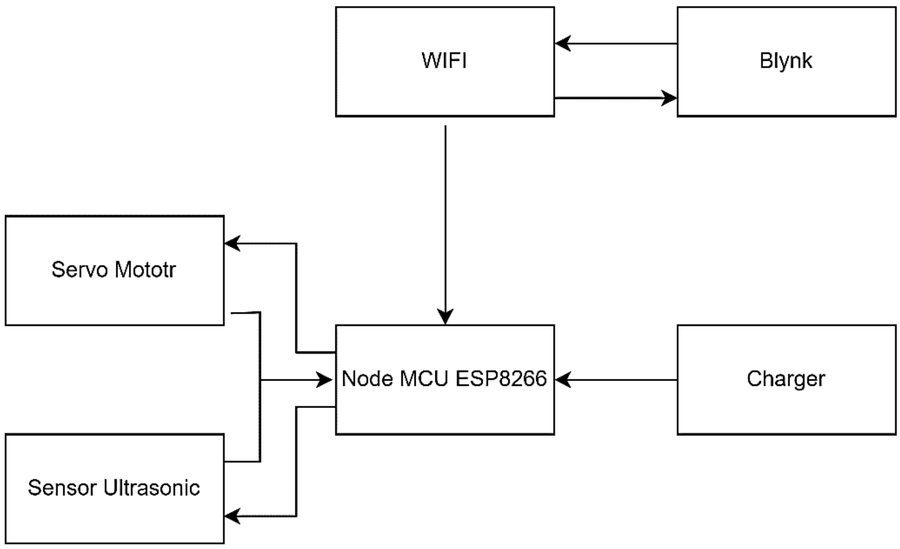

Figure 1. Block Diagram of Automatic Feeding Device

The Blynk application serves as a secondary control interface, enabling real-time monitoring of the feeding system and sending control commands to the NodeMCU over the internet. Wireless connectivity is provided via a Wi-Fi network, enabling the NodeMCU to communicate with the Blynk platform. The NodeMCU acts as the system's primary controller, responsible for processing sensor data, executing fuzzy logic decision-making, and controlling the feeding mechanism.

Sensor data is sent to the Blynk application for monitoring, while the NodeMCU executes control commands from the application. Servo motors are used as actuators to regulate the opening and closing of the feed bin. Ultrasonic sensors measure the feed level in the bin, while a power supply unit provides electrical power to ensure continuous system operation. In addition to block diagrams, flowcharts illustrate the sequential operational steps of the automatic koi fish feeding system, enabling a clear understanding of the system logic and control flow.

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Figure 2 presents the flowchart of the IoT-based automatic koi fish feeding system employing the Mamdani fuzzy logic method. The operational process begins with system initialization, followed by user access to the Blynk mobile application to enable monitoring and control functions. Subsequently, the ultrasonic sensor measures the remaining feed level inside the feed container. If the detected feed stock is classified as low, the system requires the feed container to be refilled before the feeding process can proceed. Conversely, when the feed level is identified as medium or high, the Mamdani fuzzy logic controller determines the appropriate feeding action. Based on this decision, the servo motor is activated to open and close the feed outlet, allowing a controlled amount of feed to be dispensed for the koi fish. This sequential process ensures that feeding operations are performed only when adequate feed availability is present, thereby supporting efficient and reliable automated feeding management.

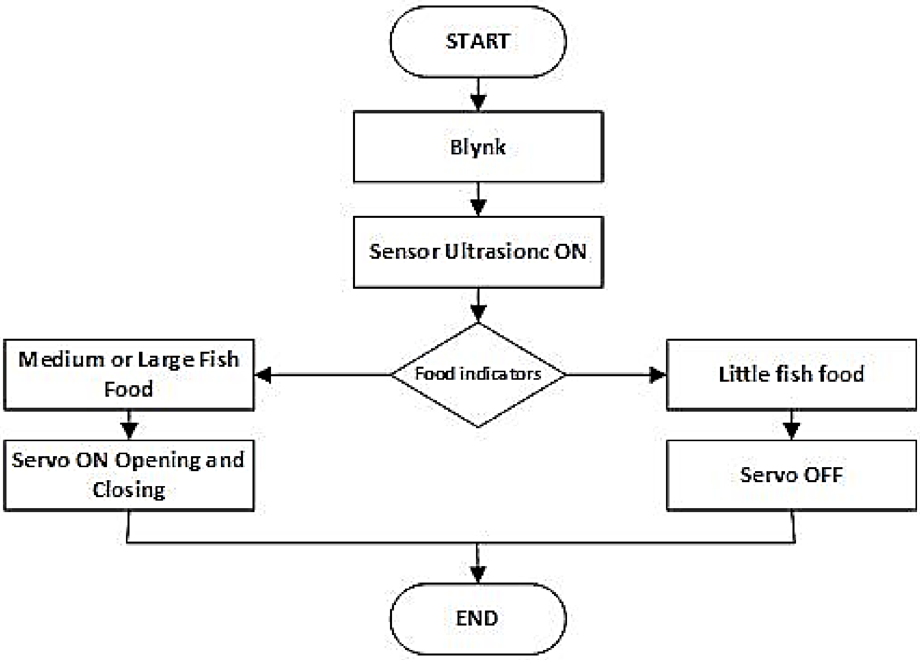

Figure 2. Flowchart Automatic Feeder

The operational process illustrated in Figure 3 shows an IoT-based automatic feeding system controlled by a NodeMCU ESP8266 microcontroller. The system begins with an ultrasonic sensor that continuously measures the distance between the sensor and the feed surface to determine the available feed level in the container. This measurement data is transmitted to the NodeMCU, where it is processed and evaluated as input variables for the control logic. Based on the interpreted feed level, the controller determines whether to initiate the feeding process. When sufficient feed is available, the NodeMCU generates a pulse width modulation (PWM) signal to drive a servo motor, which mechanically opens and closes the feed outlet to dispense the required amount of feed. Throughout the system's operation, the NodeMCU maintains wireless communication via Wi-Fi, enabling real-time monitoring and control through the IoT platform. This integrated process ensures automated, consistent, and efficient feeding while minimizing manual intervention.

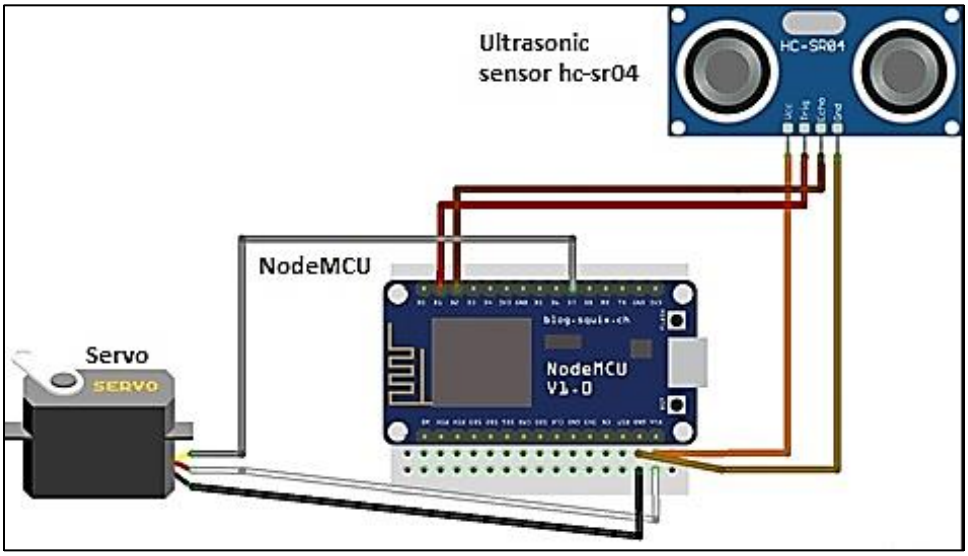

Figure 3. Automatic Feeding Tool Circuit Schematic

B. Implementation of the Mamdani Fuzzy Logic Controller

In this study, a Mamdani-type fuzzy inference system was implemented to regulate the feeding mechanism of an IoT-based automatic koi fish feeder. The primary objective of the fuzzy controller is to determine the appropriate feeding duration based on the remaining feed level measured inside the storage container. The Mamdani approach was selected due to its interpretability and suitability for decision-making problems involving linguistic rules and imprecise data. The fuzzy system consists of one input variable, namely feed level, obtained from an ultrasonic sensor and expressed as a percentage (%), and one output variable, namely feeding duration, which controls the servo motor opening time. Feed level is important for feeding decisions; without it, the system will not function well. From a control perspective, a higher feeding level allows a longer feeding duration. If the feed is insufficient, a longer feeding duration will require more energy to move the motor. Thus, adjusting feeding duration based on feeding level will improve power efficiency.

The input variable is defined by three fuzzy sets, namely Low feed level, medium feed level, and High feed level. The membership functions for these fuzzy sets are described in Equation (1), Equation (2), and Equation (3) respectively.

Low feed level $$\mu_L(x) = \begin{cases} 1, & x \leq 40 \\ \dfrac{60 - x}{60 - 40}, & 40 < x < 60 \\ 0, & x \geq 60 \end{cases} \tag{1}$$

Medium feed level: $$\mu_M(x) = \begin{cases} 0, & x \le 40 \text{ or } x \ge 60 \\ \dfrac{x-40}{60-40}, & 40 < x \le 50 \\ \dfrac{60-x}{60-50}, & 50 < x < 60 \end{cases} \tag{2}$$

High feed level: $$\mu_H(x) = \begin{cases} 0, & x \le 60 \\ \dfrac{x-60}{100-60}, & 60 < x < 100 \\ 1, & x \ge 100 \end{cases} \tag{3}$$

These membership functions are represented using triangular and trapezoidal shapes to ensure smooth transitions between easily distinguishable categories. The output variable is also described using three fuzzy sets: Short, Moderate, and Long feeding durations, corresponding to servo activation times of approximately 3, 4, and 5 seconds, respectively. These values were determined empirically based on feeding requirements and system responsiveness. These three options ensure that the feeding process will neither be too little nor too much. If the feed is less than the required portion, then the Koi Fish will starve. On the contrary, overfeeding Koi Fish will slowly kill the fish. Thus, appropriately adjusting feeding duration will help Koi live longer.

The fuzzy inference process follows four main stages. First, fuzzification converts crisp input values from the ultrasonic sensor into degrees of membership across the defined fuzzy sets. Second, rule evaluation is performed using a set of linguistic IF–THEN rules derived from expert knowledge. For example: IF feed level is Low THEN feeding duration is Long. Third, aggregation combines the outputs of all activated rules using the maximum (max) operator. Finally, defuzzification is carried out using the centroid method to obtain a crisp output value representing the final feeding duration. Experimental results demonstrate that the Mamdani fuzzy controller produces smooth and adaptive feeding decisions under varying feed-level conditions. The implementation effectively prevents underfeeding and overfeeding, thereby improving feeding consistency and supporting healthier koi fish maintenance.

IV. RESULT

A. Result

The proposed IoT-based automatic feeding system for Koi fish using the Mamdani Fuzzy Logic method was successfully implemented and operated as designed. The system integrates a NodeMCU ESP8266 microcontroller, an ultrasonic sensor for feed-level detection, a servo motor for feed dispensing, and the Blynk IoT platform for remote monitoring. The NodeMCU reliably performed data acquisition, fuzzy inference processing, and cloud data transmission via Wi-Fi. The Blynk application provided real-time visualization of feed stock levels and supported both manual and scheduled feeding control through mobile and web interfaces. Feedstock measurements were evaluated using manual, digital ruler, and ultrasonic sensor methods, with results summarized in Tables 1, 2, and 3.

Table 1. Manual Feed Level Measurement Results

Feed Volume (ml)	Measured Height (cm)
0	19.0
220	16.5
440	13.3
660	10.0
880	7.3

Table 2. Digital Ruler Measurement Results

Feed Volume (ml)	Measured Height (cm)
0	19.2
220	16.5
440	13.6
660	10.2
880	7.5

Table 3. Ultrasonic Sensor Measurement Results

Feed Volume (ml)	Measured Height (cm)
0	19.0
220	16.2
440	13.6
660	10.1
880	7.1

The ultrasonic sensor's measurement accuracy was evaluated by comparing its readings with reference measurements. The calculated error values are summarized in Table 4. The fuzzy logic system was configured with one input and one output variable, as shown in Table 5. The fuzzy inference system employed three primary rules, summarized in Table 6.

Table 4. Measurement Error Evaluation

No	Reference Height (cm)	Digital Error (cm)	Ultrasonic Error (cm)	Average Error (cm)	Error (%)
1	19.0	0.2	0.0	0.10	0.53
2	16.5	0.0	0.3	0.15	0.91
3	13.3	0.3	0.3	0.30	2.26
4	10.0	0.2	0.1	0.15	1.50
5	7.3	0.2	0.2	0.20	2.74

Average Measurement Error: 1.59%

Table 5. Fuzzy Logic Variables

Variable Type	Linguistic Term	Range
Input (Feed Level)	Low	0–40%
	Medium	40–60%
	High	60–100%
Output (Feeding Duration)	Short	0–22.3
	Medium	22.3–77.7
	Long	77.7–100

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Table 6. Fuzzy Rule Base

Rule No	Feed Level	Feeding Duration
1	Low	Long (5 seconds)
2	Medium	Medium (4 seconds)
3	High	Short (3 seconds)

System testing was conducted using real feed level data as input. The fuzzy logic outputs are presented in Table 7. Automatic feeding was executed twice daily at 08:00 WIB and 15:00 WIB. The servo motor successfully dispensed feed at each scheduled time without execution failure. Manual feeding via the Blynk application also operated correctly according to the fuzzy-logic-defined feeding durations.

Table 7. Fuzzy Logic Test Results

Test No	Input Feed Level (%)	Output (%)	Feed Category
1	55.3	61.3	High
2	40.1	22.7	Low
3	50.2	50.7	Medium

The X-axis (input1) represents the percentage of remaining feed, ranging from 0% to 100%. The Y-axis (output1) represents the feed duration measured in seconds, which determines how long the servomotor dispenses feed. The curve exhibits a non-linear mapping: for low input values (below approximately 35%), the output duration increases slowly. As the input value rises above 35%, the output duration increases more sharply, indicating that the less feed remaining, the longer the dispensing time.

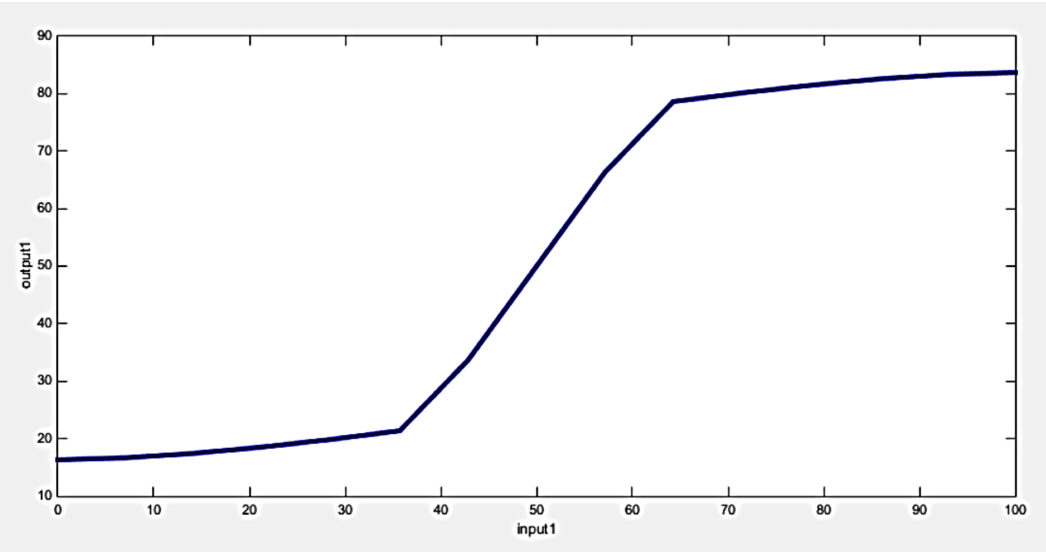

Figure 4. Graph Fuzzy

For high input values (above approximately 65%), the output duration reaches a saturation point, indicating that when raw material is abundant, the system dispenses feed for a consistent maximum duration. This behavior aligns with the fuzzy rules defined in the thesis, where a "small" feed results in a longer feed time (5 seconds), a "medium" feed results in a moderate time (4 seconds), and a "large" feed results in a shorter time (3 seconds), as shown in Figure 4.

Discussion

This section explains the strengths and weaknesses, compares with the previous model, and outlines future work. The first discussion is about the strength of the proposed model. Based on the error evaluation results, the proposed model achieved an error rate of 1.59%. This result indicates that the proposed model provides an appropriate portion with minimal error during feeding. Thus, the proposed model used power efficiently only when the feed level was sufficient. Despite having strengths, this model also has weaknesses that need to be considered. The weakness is the algorithm itself. The fuzzy Mamdani algorithm is sensitive to changes, and a small change in membership may affect the result. Thus, the model must be configured as accurately as possible to reduce incorrect output.

The second discussion compares the current model with the previous model. As explained in the introduction, existing models typically support only predefined, threshold-based feeding. This study improves the existing model by implementing a Fuzzy Mamdani method to determine the feeding portion based on opening duration. The previous models only provided a fixed portion and could not determine their available feed level, reporting an empty tank only when the feed was running out. On the contrary, the proposed model can adjust the feed portion based on the tank level. Not only does the proposed model intelligently adjust the portion, but it also uses power more efficiently than the previous model.

The third discussion is scalability and deployment: the model could be expanded by adding more sensors to monitor water quality. However, this model is limited to one model per aquarium. Thus, expanding deployment across many models requires specialized data-aggregation processing. This special node is often expensive and requires more power. In addition to supporting Koi Fish feeding, the proposed model can be used in other aquariums with minor adjustments based on the number of inhabitants, the types of fish, and the feed. If the feed fits the feeder tank, then the proposed model will work. Only a small code adjustment is required to change the duration range. Thus, the proposed model can generally be used in many different fish aquariums. The proposed model is simple and can be adjusted to meet specific needs. Besides supporting Koi Fish feeding, the proposed model can be used in other aquariums with minor adjustments based on the number of inhabitants, the types of fish, and the feed. If the feed fits the feeder tank, then the proposed model will work. Only a small code adjustment is required to change the duration range. Thus, the proposed model can generally be used in many different fish aquariums.

The final section discusses the future work of this study. For future work, many improvements can be made to the system. In this case, a better decision-support algorithm is needed to make more accurate decisions based on the condition at hand. A lightweight algorithm, such as a decision tree, Random Forest, or an Ensemble algorithm, is recommended for the model, as they provide better accuracy and precision.

V. CONCLUSION

This study successfully developed and evaluated an Internet of Things (IoT)-based automatic feeding system for Koi fish by integrating a NodeMCU ESP8266 microcontroller, an ultrasonic sensor, a servo motor, and the Blynk IoT platform, with feeding decisions governed by the Mamdani Fuzzy Logic method. Experimental results demonstrated that the ultrasonic sensor achieved reliable feed level detection with an average measurement error of 1.59%, indicating adequate accuracy for practical aquaculture applications. The fuzzy logic controller effectively converted feed level information into adaptive feeding durations, enabling consistent feed distribution while reducing the risk of overfeeding or underfeeding. Automatic feeding schedules were executed reliably at predefined times, and manual feeding control via a mobile interface operated responsively without significant delay. Overall, the proposed system enhances feeding consistency, minimizes human dependency, and supports healthier Koi fish maintenance in small-scale ornamental aquaculture.

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REFERENCES

Amarudin, A., Saputra, D. A., & Rubiyah, R. (2020). Design and Development of an Automatic Fish Feeding System Using a Microcontroller. *Jurnal Ilmiah Mahasiswa Kendali Dan Listrik*, *1*(1), 7–13. https://doi.org/10.33365/jimel.v1i1.231

Andrian, K. N., Wihadmadyatami, H., Wijayanti, N., Karnati, S., & Haryanto, A. (2024). A Comprehensive Review of Current Practices, Challenges, and Future Perspectives in Koi Fish (Cyprinus Carpio var. Koi) Cultivation. *Veterinary World, 17*(8), 1846–1854. https://doi.org/10.14202/vetworld.2024.1846-1854

Belgacem, H., & Chihi, I. (2025). Toward Reliable and Intelligent Sensor Systems: A Comprehensive Study of Fault Diagnosis and Mitigation. *IEEE Sensors Reviews, 2*, 511–536. https://doi.org/10.1109/sr.2025.3601092

Choudhary, A., Mian, T., & Fatima, S. (2021). Convolutional Neural Network Based Bearing Fault Diagnosis of Rotating Machine Using Thermal Images. *Measurement, 176*, 109196. https://doi.org/10.1016/j.measurement.2021.109196

Daru, A. F., Susanto, S., & Adhiwibowo, W. (2024). Arowana Cultivation Water Quality Monitoring and Prediction Using Autoregressive Integrated Moving Average. *International Journal of Reconfigurable and Embedded Systems, 13*(3), 665–672. https://doi.org/10.11591/ijres.v13.i3.pp665-672

Firmansyah, M. P., Nashir, M. N., Rahmeisi, N., Augusta, P. S., & Arfriandi, A. (2026). Tinjauan Literatur Sistematis tentang Deteksi Anomali Berbasis Kecerdasan Buatan untuk Intrusi Jaringan pada IoT. *Jurnal Ilmiah Sistem Informasi*, *5*(1), 71–83. https://doi.org/10.51903/eqne0j35

Ibrahim, S. M., Go, E.-M., & Iranda, J. (2024). Scalable and Secure IoT-Driven Vibration Monitoring: Advancing Predictive Maintenance in Industrial Systems. *Journal of Technology Informatics and Engineering*, *3*(3), 370–381. https://doi.org/10.51903/jtie.v3i3.210

Kusrini, E., Cindelaras, S., & Prasetio, A. B. (2015). Development of Ornamental Fish Aquaculture Technology in Indonesia. *Indonesian Aquaculture Journal, 10*(2), 101–110. https://doi.org/10.15578/iaj.10.2.2015.101-110

Li, L., Zhang, Q., & Huang, D. (2020). A Review of Imaging Techniques for Plant Phenotyping. *Sensors*, *20*(9), 2674. https://doi.org/10.3390/s20092674

Mase, E. M., Witi, F. W., & Bhae, B. Y. (2025). Optimalisasi Pemantauan Level Air dalam Bak Penampungan Air Menggunakan Internet of Things (IOT) di Universitas Flores. *Jurnal Ilmiah Sistem Informasi*, *4*(1), 163–179. https://doi.org/10.51903/4xg62v92

Mohamed, A. A., Muhammad, N. A. B., Rashid, R. A., Ahmed, M. M., Ali, A. A., & Abdikadir, N. M. (2024). IOT-Based Automatic Fish Feeding System. *2024 IEEE 22nd Student Conference on Research and Development (SCOReD)*, 333–338. https://doi.org/10.1109/scored63310.2024.10861942

Mudholkar, P., Mudholkar, M., Jijaba, K. J., & Kalita, J. P. (2025). Smart Aquaculture: IoT, Cloud Computing, and AI for Sustainable Fisheries. *Vascular and Endovascular Review, 8*(17s), 383–391. https://doi.org/10.15420/ver.2024.67

Nagothu, S. K., Bindu Sri, P., Anitha, G., Vincent, S., & Kumar, O. P. (2025). Advancing Aquaculture: Fuzzy Logic-Based Water Quality Monitoring and Maintenance System for Precision Aquaculture. *Aquaculture International, 33*(1), 32. https://doi.org/10.1007/s10499-024-01532-7

Nanjar, A., Maharani, T. S., Prastyo, P. A., Hidayat, M. T. N., & Najibulloh, I. kharits. (2024). Internet of Things (IoT) Integration in Telecommunication Networks: Challenges and Opportunities. *Journal of Technology Informatics and Engineering*, *3*(1), 11–24. https://doi.org/10.51903/jtie.v3i1.156

Noor, M. Z. H., Hussian, A. K., Saaid, M. F., Ali, M. S. A. M., & Zolkapli, M. (2012). The Design and Development of Automatic Fish Feeder System Using PIC Microcontroller. *2012 IEEE Control and System Graduate Research Colloquium*, 343–347. https://doi.org/10.1109/csgrc.2012.6259132

Papini, N., Rugini, L., Cecconi, M., Scorzoni, A., Tarantino, A., & Placidi, P. (2025). Measurement-Based Model for Water Content Estimation in Sustainable Granular Materials Using an IoT Custom Device. *IEEE Transactions on Instrumentation and Measurement*, *74*, 1-9. https://doi.org/10.1109/tim.2025.1234567

Prapti, D. R., Mohamed Shariff, A. R., Che Man, H., Ramli, N. M., Perumal, T., & Shariff, M. (2022). Internet of Things (IoT)-Based Aquaculture: An Overview of IoT Application on Water Quality Monitoring. *Reviews in Aquaculture, 14*(2), 979–992. https://doi.org/10.1111/raq.12675

Pribadi, W., Prasetyo, Y., & Juliando, D. E. (2020). Design of Fish Feeder Robot Based on Arduino-Android With Fuzzy Logic Controller. *Int. Res. J. Adv. Eng. Sci, 5*(4), 47–50. https://doi.org/10.21776/ub.irjaes.2020.005.04.07

Singh, R. K., Berkvens, R., & Weyn, M. (2021). AgriFusion: An Architecture for IoT and Emerging Technologies Based on a Precision Agriculture Survey. *IEEE Access, 9*, 136253–136283. https://doi.org/10.1109/access.2021.3118814

Susilo, B. W., & Susanto, E. (2024). Employing Artificial Intelligence in Management Information Systems to Improve Business Efficiency. *Journal of Management and Informatics*, *3*(2), 212–229. https://doi.org/10.51903/jmi.v3i2.30

Sutabri, T., Octavianto, T., & Widodo, Y. B. (2021). Fuzzy Logic-Based Automatic Feeding System for Ornamental Fish Using IoT Technology. *Journal of Telecommunication, Electronic and Computer Engineering, 13*(2), 45–52. https://doi.org/10.11591/jtec.v13i2.25258

Tang, J., Alelyani, S., & Liu, H. (2014). Feature Selection for Classification: A Review. In H. Liu & H. Motoda (Eds.), *Feature Selection for Data and Pattern Recognition*, 37–64. https://doi.org/10.1007/978-3-642-41836-6_3

Tarihoran, A. D. B., Hubeis, M., Jahroh, S., & Zulbainarni, N. (2024). Building a Sustainable Institutional Model for Ornamental Fish Farming Export Villages in Indonesia. *International Journal of Agricultural Sustainability, 22*(1), 2401203. https://doi.org/10.1080/14735903.2024.2401203

Xu, P., Xu, H., Xiao, P., & Guo, Z. (2026). Multisensor Visual Cognition Framework-Supported Intelligent Feeding Approach for Industrial Aquaculture. *IEEE Sensors Journal, 26*(2), 2955–2969. https://doi.org/10.1109/jsen.2025.3156247

Zhou, C., Lin, K., Xu, D., Chen, L., Guo, Q., Sun, C., & Yang, X. (2018). Near Infrared Computer Vision and Neuro-Fuzzy Model-Based Feeding Decision System for Fish in Aquaculture. *Computers and Electronics in Agriculture, 146*, 114–124. https://doi.org/10.1016/j.compag.2018.02.006