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Design of A Smart Cat Feeding System Using The Sugeno Fuzzy Logic Method Within An IoT Framework

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ABSTRACT

The increasing number of cat owners often conflicts with busy schedules, leading to irregular feeding and health risks like obesity or malnutrition. Current automatic feeding systems are generally schedule-based without adjusting portions to individual nutritional needs. This study aims to design an Internet of Things (IoT)-based automatic cat feeder system integrating the Sugeno Fuzzy Logic method to determine feed portions adaptively. The system utilizes a NodeMCU ESP32 as the main controller, three load cells to weigh the cat, food portion, and remaining water, alongside an HC-SR501 PIR sensor detecting daily activity levels. The input variables for fuzzy logic include age, body weight, and activity level, which produce a specific feed portion output (Small 35g, Medium 70g, Large 105g) using an auger drive mechanism. Test results indicate highly precise performance. Weighing accuracy reached 98.62% for cat weight, 98.63% for food portions, and 98.87% for water volume. Furthermore, validating the Sugeno Fuzzy Logic algorithm on the microcontroller against MATLAB simulations yielded a 100% accuracy rate with zero computational error (MSE=0, RMSE=0, R^2=1). Feed realization by the actuator achieved 98.85% accuracy. The system proved reliable in maintaining punctuality with an average delay of 11.07 seconds, demonstrating good network resilience through local storage during offline states. This implementation facilitates owners in preventively maintaining the welfare and nutritional balance of their pet cats.

1. INTRODUCTION

The pet food sector has experienced massive global growth in recent years, highlighting the reality that domestic cats have become integral, valued members of modern urban households [1]. However, the rising feline population also introduces significant urban challenges, ranging from the rapid multiplication of stray cats to their emerging role as prominent symbols in various socio-political issues [2], [3]. In the context of domestic pet care, regular and nutritionally balanced feeding is a critical responsibility. A lack of precise dietary management is a primary catalyst for severe health anomalies, including feline obesity, malnutrition, and complex metabolic disorders [4], [5].

Veterinary nutritional standards emphasize that food portions cannot be static; they must be dynamically adjusted based on a cat's individual physical conditions [6]. The calculation of feline energy requirements heavily relies on the Resting Energy Requirement (RER) and the Maintenance Energy Requirement (MER), which are dictated by variables such as body weight, age (life stage), and daily physical activity levels [7]. Despite these rigorous guidelines, many modern pet owners are constrained by high-mobility lifestyles and tight working schedules, resulting in irregular feeding habits or unintentional overfeeding.

Commercially available automatic cat feeders attempt to bridge this gap by offering scheduled feeding mechanisms [8], [9]. However, most basic automated devices operate strictly on fixed timers and predetermined volumetric outputs. They lack the intelligence to dynamically assess the pet's current physiological needs. Recent technological advancements have demonstrated the viability of microcontroller-based, internet-connected feeding devices. Systems utilizing the Wemos D1 Mini and ESP8266 microcontrollers have successfully allowed remote configuration via platforms like Telegram and Blynk, although some face signal latency and stability issues during manual operations [10], [11]. Further developments introduced the ESP32 microcontroller paired with weight sensors to log feeding times, alongside mechanisms utilizing ultrasonic sensors to control servo motors or actuators [12]–[13][14].

To move beyond simple scheduling and achieve true automation, artificial intelligence must be implemented. Fuzzy logic inference systems have been applied in theoretical simulations and basic prototypes to determine appropriate dry food portions based on linguistic variables like age and weight, showcasing high computational adaptability [15], [16], [17], [18]. The application of fuzzy logic ensures that decision-making remains objective, robust against noise, and scalable across various evaluation parameters [19].

This study aims to design an Internet of Things (IoT)-based automatic cat feeder system integrating the Sugeno Fuzzy Logic method to determine feed portions adaptively. Building upon these foundational studies, this research designs and implements an advanced, adaptive smart cat feeding system utilizing the NodeMCU ESP32 and the Zero-Order Sugeno Fuzzy Logic method within an IoT framework. Unlike previous prototypes, this system integrates periodic body weight measurement via a dedicated weighing platform, precise portion control utilizing an auger mechanism, and real-time activity level detection using a PIR sensor to dynamically calculate and dispense optimal nutritional portions.

2. METHODS

To ensure the smart cat feeding system functions effectively and adapts to the dynamic needs of pets, a well-structured methodological approach is required to bridge the gap between physical sensor data and intelligent decision-making. Therefore, the system's operational workflow is divided into hardware execution and software logic processing. The ESP32 continuously polls the RTC to check if the current time matches the user-defined feeding schedules synchronized via the Firebase Realtime Database. Once a scheduled time is reached,

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the system initiates the feeding protocol.

2.1 Hardware Architecture and Core Components

The hardware architecture comprises several integrated electronic modules designed for precision measurement, mechanical actuation, and continuous IoT connectivity.

2.1.1. NodeMCU ESP32

Serving as the central processing unit, the ESP32 (**Figure 1**) utilizes its dual-core processor to handle fuzzy logic operations locally. Its built-in Wi-Fi module ensures real-time data synchronization with the Firebase Realtime Database, allowing users to monitor the system via a web interface.

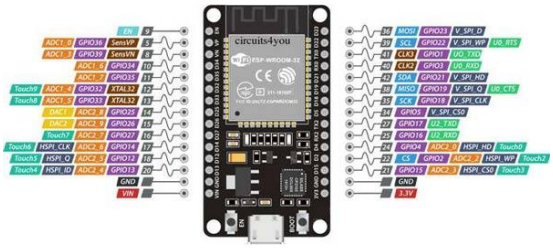


Figure 1. NodeMCU ESP32

2.1.2. UPS Module

To guarantee reliability and fault tolerance during grid power outages, the subsystem includes a 12V Uninterruptible Power Supply (UPS) (shown in **Figure 2**) module equipped with 18650 lithium-ion batteries [20], [21]. A step-down DC-DC buck converter (5V 3A) regulates the voltage to safely power the microcontroller and peripheral sensors, ensuring high efficiency and low thermal loss [22].



Figure 2. UPS Module

2.1.3. Load Cell with HX711 Module

Quantitative mass measurement is facilitated by three strain-gauge load cells (**Figure 3**) designed to monitor axial forces [23], [24]. Load Cell 1 is placed under a dedicated platform to measure the cat's body weight. Load Cell 2 records the dispensed food portion in the feeding bowl, and Load Cell 3 monitors the remaining water volume. These sensors are paired with HX711 24-bit analog-to-digital converters to amplify the microvolt signals.

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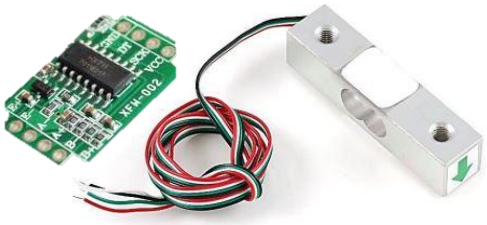


Figure 3. Load Cell with HX711 Module

2.1.4. Ultrasonic Sensor HY-SRF05

An HY-SRF05 (**Figure 4**) ultrasonic sensor is securely mounted inside the main hopper to accurately detect the physical level of the stored dry food. This sensor operates by measuring the distance between the top of the container and the surface of the kibble, allowing the microcontroller to continuously estimate the remaining food volume. By monitoring this spatial data in real-time, the system can autonomously trigger low-stock alerts and send push notifications to the user's mobile dashboard, ensuring the food supply is consistently replenished before it runs out.



Figure 1. Sensor HY-SRF05

2.1.5. PIR Sensor HC-SR501

An HC-SR501 Passive Infrared (PIR) sensor is strategically positioned to monitor the cat's daily physical activity (**Figure 5**). Operating in a specifically calibrated non-repeatable trigger mode with a defined delay to prevent double-counting, this sensor detects movement based on the thermal infrared energy emitted by the cat's body. The cumulative daily activity data recorded by this sensor is a crucial component of the system, as it serves as one of the primary input variables for the fuzzy logic engine to accurately determine the optimal caloric requirement and subsequent food portion for the day.



Figure 2. Sensor HC-SR501

2.1.6. DC Motor 5V

For the feeding mechanism, a 5V DC motor equipped with a 240 RPM gearbox (**Figure 6**) serves as the primary mechanical actuator. This motor drives a spiral auger mechanism specifically designed to push the dry kibble out of the hopper and into the feeding bowl. Unlike

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traditional flap-servo mechanisms that are prone to jamming or sudden, inaccurate dumps of food, the auger allows for a highly controlled, gradual dispensing process [14]. The motor's active duration is dynamically adjusted by the microcontroller based on the precise gram target calculated by the fuzzy logic system.



Figure 3. DC Motor 5V

2.1.7. Water Pump Actuator

A 5V mini DC water pump as shown in **Figure 7**, controlled via a dedicated relay module, handles the automated refilling of the cat's water bowl. This electromagnetic pump was selected for its low power consumption and seamless compatibility with the ESP32 logic levels. When the dedicated load cell detects that the remaining water volume has dropped below a predefined safety threshold during its scheduled periodic checks, the microcontroller signals the relay to activate the pump, automatically restoring the water level to ensure the pet remains properly hydrated without requiring manual intervention.

2.2. Zero-Order Sugeno Fuzzy Logic Design



Figure 7. Water Pump Actuator

To determine the optimal food portion, the system relies on an embedded Zero-Order Sugeno Fuzzy Logic inference engine written in C++. The controller utilizes three main input variables: Age, Body Weight, and Activity Level.

2.2.1. Fuzzification

Crisp inputs are mapped into fuzzy sets using trapezoidal and triangular membership functions. The 'Age' variable is categorized into Kitten (0-0.6 years), Adolescent (0.5-1 years), and Adult (0.75-7 years). The 'Weight' variable is classified into Light (0.1-3 kg), Normal (2.5-4.5 kg), and Heavy (4.2-7 kg). The 'Activity Level', acting as a multiplier, is mapped into Inactive (1.1-1.15), Moderately Active (1.1-1.3), and Very Active (1.25-1.5).

2.2.2. Rule Base and Inference

The inference engine processes these inputs through a comprehensive rule base consisting of 27 IF-THEN rules covering all physiological combinations. For instance: IF Age is Kitten AND Weight is Light AND Activity is Very Active, THEN Portion is Large.

2.2.3. Deffuzification

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In the Sugeno method, consequents are defined as crisp constants. The output portions are defined as Small (35g), Medium (70g), and Large (105g). The final output is calculated using the Weighted Average method, producing a single numerical value representing the target grams to be dispensed by the auger mechanism.

2.3. Evaluation Metrics

To validate the computational accuracy of the embedded C++ algorithm on the ESP32, the system's output predictions were statistically compared against theoretical ground truth values generated via MATLAB Fuzzy Logic Designer. Performance was evaluated using Mean Square Error (MSE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R-Square) [25]. The mathematical representations and brief explanations for these metrics are as follows:

2.3.1. Mean Square Error (MSE)

Measures the average of the squared differences between the predicted outputs (X_i) and the actual ground truth values (Y_i) [25].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)^2 \quad (1)$$

2.3.2. Root Mean Square Error (RMSE)

Represents the square root of the MSE, which reduces the squared effect and provides the error magnitude in the original continuous unit[25].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)^2} \quad (2)$$

2.3.3. Coefficient of Determination *(R^2)*

Evaluates the proportion of the variance in the target variable that can be explained by the model, where $\bar{X}$ is the average of the predicted data [25].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - X_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{X})^2} \quad (3)$$

Furthermore, a multi-class Confusion Matrix was employed to evaluate classification performance. The metrics calculated include Accuracy, Precision, Recall (Sensitivity), and the F1-Score, utilizing macro-averaging to account for potential class distribution imbalances [25]. These metrics are defined based on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) as follows:

2.3.4. Accuracy

Measures the overall correctness of the model's predictions by calculating the ratio of correct predictions to the total number of cases [25].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

2.3.5. Precision

Indicates the proportion of positive predictions that are actually correct, reflecting the model's confidence in identifying true positives [25].

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

2.3.6. Recall

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Measures the model's capability to correctly identify and cover all actual true positive instances within the dataset [25].

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

2.3.7. F1-Score

Provides a harmonic mean that balances Precision and Recall, which is particularly useful for achieving equilibrium in imbalanced datasets [25].

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

Hardware accuracy was additionally evaluated by comparing the physical sensor readings against validated commercial digital scales to ensure real-world implementation precision.

3. RESULTS AND DISCUSSION

3.1. Hardware Implementation and Web Interface

The prototype successfully integrated the storage compartments, the auger dispensing mechanism, and the sensor modules into a cohesive physical unit. The separate weighing platform allows the system to capture the cat's body weight securely during the active feeding window. The software interface was developed as a responsive web application linked to Firebase, featuring token-based authentication. The dashboard provides users with real-time visualizations of remaining food stock, cumulative daily intake, activity counts, and active feeding schedules. The physical prototype of the Smart Feeder and dashboard of this system are shown in **Figure 8** and **Figure 9**.



Figure 8. Physical Prototype of the Smart Feeder

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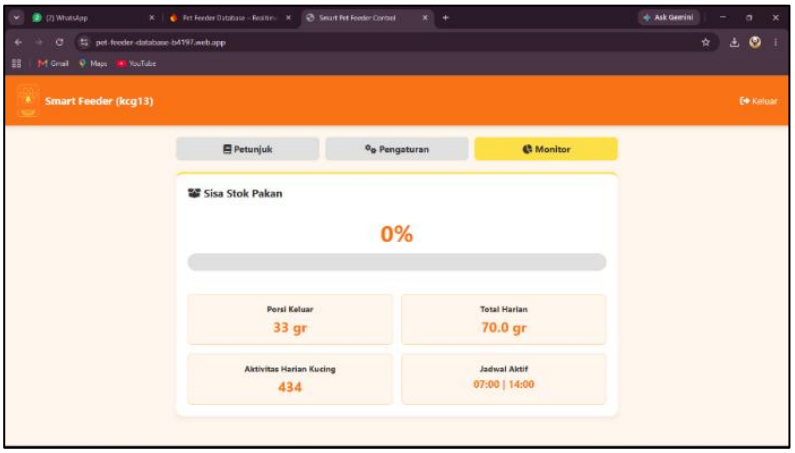


Figure 9. Real-time Web Dashboard

3.2. Sensor Accuracy Evaluation

Extensive calibration and testing were conducted to validate the precision of the mass measurement sensors. Each of the three load cells was tested across 20 distinct mass samples ranging from 3 grams to 60 grams, utilizing a validated commercial scale as the ground truth. Multiple calibration techniques applying linear regression ($y = mx + c$) corrected systematic deviations.

Tabel 1. Summary of Load Cell Measurement Accuracy

Sensor Unit	Function	Average Error Rate (%)	Overall Accuracy (%)
Load Cell 1	Cat Body Weight	1.38%	98.62%
Load Cell 2	Food Portion	1.37%	98.63%
Load Cell 3	Water Volume	1.13%	98.87%

Load Cell 1 (Cat Weighing Platform) demonstrated outstanding precision with an average error rate of only 1.38% and an overall accuracy of 98.62%. Minor under-reading was observed at lower mass limits, which is characteristic of high-capacity load cells, but remains well within acceptable operational tolerances. Load Cell 2 (Food Dispenser) recorded an average error rate of 1.37% (98.63% accuracy). The highest recorded error of 8.33% occurred at a very light 6-gram load, primarily due to the uneven distribution of kibble dropping onto the bowl. Load Cell 3 (Water Monitor) showed a consistent, slight overshoot characteristic, yielding an average error of 1.13% and an accuracy of 98.87%, perfectly adequate for triggering the water refill pump accurately.

The HY-SRF05 ultrasonic sensor used for stock monitoring was evaluated over distances from 4 cm to 28 cm. The test revealed an average error rate of 0.84% and an accuracy of 99.15%. A notable deviation (5% error) occurred at the absolute minimum distance of 4 cm due to the physical blind spot inherent in ultrasonic transducers. Nevertheless, for the purpose of estimating general stock levels and triggering low-stock notifications, this accuracy is highly reliable.

3.3. IoT Reliability and Actuation Delay

Evaluating the synchronization between cloud-based scheduling and hardware execution is vital for IoT automation. Testing across 10 different schedule points revealed actuation delays ranging from 5.49 seconds to 17.83 seconds, culminating in an average response time of 11.07 seconds. This minimal delay is attributed to the internal polling cycles and the fuzzy logic computation overhead within the ESP32. In the context of pet feeding, an 11-second

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delay is negligible, classifying the system's execution as highly punctual.

Network resilience was tested by intentionally severing the Wi-Fi connection. The system demonstrated excellent fault tolerance; it seamlessly transitioned to offline mode, relying on the RTC and locally cached schedules to dispense food without interruption. Upon network restoration, the ESP32 successfully auto-reconnected within approximately 10 seconds and synchronized the pending feeding logs back to Firebase without data loss.

3.4. Validation of the Sugeno Fuzzy Logic Method

The core intelligence of the system the embedded Sugeno Fuzzy Logic inference engine was rigorously validated against a theoretical simulation in MATLAB. The dataset comprised 28 daily records from two active test subjects (Cat A: 0.4 years, Cat B: 1.0 years).

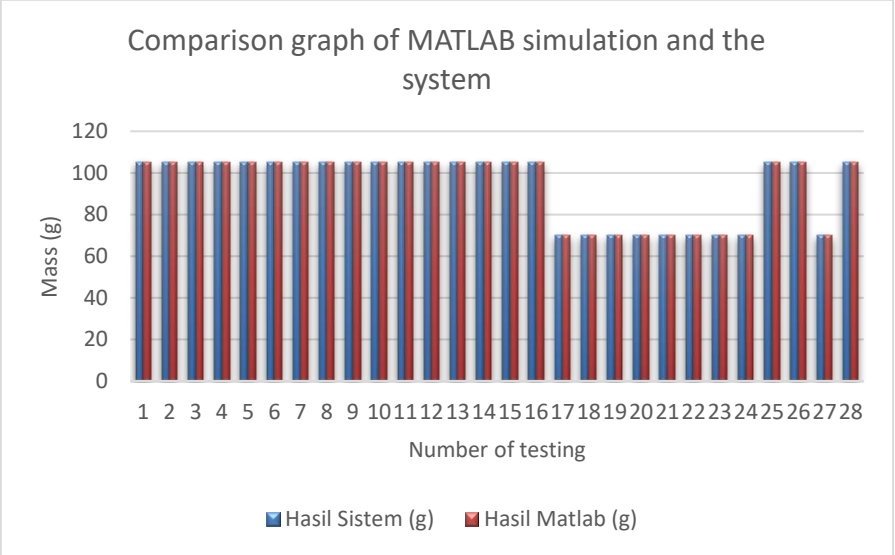


Figure 10. Comparison Graph Simulation and the System

Comparison Graph Simulation and the System is expalained in **Figure 10**. The comparative mathematical analysis yielded exceptional results. Across all 28 test iterations ($n = 28$), the crisp output from the ESP32 (X_i) perfectly matched the MATLAB theoretical output (Y_i), resulting in a difference of zero for every sample ($(Y_i - X_i) = 0$). Consequently, the Mean Square Error (MSE) and Root Mean Square Error (RMSE) calculations yielded an absolute zero:

$$MSE = \frac{1}{28}\sum_{i=1}^{28}(0)^2 = 0 \tag{8}$$

$$RMSE = \sqrt{0} = 0 \tag{9}$$

Similarly, the R-Square (R^2) metric achieved a perfect score of 1, as the error variance in the numerator evaluates to zero:

$$R^2 = 1 - \frac{0}{\sum_{i=1}^{28}(Y_i - \bar{X})^2} = 1 \tag{10}$$

These results empirically prove that the embedded C++ algorithm executes the zero-order Sugeno logic, rule aggregation, and weighted average defuzzification without any floating-point anomalies or logical deviations.

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Tabel 2. Confusion Matrix

Prediction/Actual		Actual		
		Small	Medium	Large
Prediction	Small	0	0	0
	Medium	0	9	0
	Large	0	0	19

To evaluate the classification performance **Table 2**, a multi-class Confusion Matrix was utilized, mapping the output into three categories: Small, Medium, and Large. Using a One-vs-Rest approach, the values for True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) for each class are detailed as follows:

- Small Portion (35g) Class: The system correctly identified zero instances as Small (TP = 0), as there were no actual Small targets in the dataset. There were zero instances incorrectly predicted as Small (FP = 0) and zero actual Small instances missed (FN = 0). The system correctly identified 28 instances as not Small (TN = 28).
- Medium Portion (70g) Class: The system correctly predicted 9 actual instances as Medium (TP = 9). It made zero incorrect Medium predictions (FP = 0) and missed zero actual Medium instances (FN = 0). It correctly identified 19 instances as not Medium (TN = 19).
- Large Portion (105g) Class**:** The system accurately predicted 19 actual instances as Large (TP = 19). There were zero incorrect Large predictions (FP = 0) and zero actual Large instances missed (FN = 0). It correctly recognized 9 instances as not Large (TN = 9).

Based on the mapped Confusion Matrix, the classification performance is quantitatively evaluated. For a multi-class scenario, the overall Accuracy is calculated as the ratio of total correct predictions to the total dataset:

$$Accuracy = \frac{TP_{total}}{Total\ Data} = \frac{0 + 9 + 19}{28} = 1\ (100\%)$$

Precision and Recall are calculated using a macro-average approach, taking the average of the metrics for each individual class ($n = 3$):

$$Precision_{macro} = \frac{\sum\left(\frac{TP}{TP + FP}\right)}{n_{classes}} = \frac{0 + 1 + 1}{3} = 0.667\ (66.7\%)$$

$$Recall_{macro} = \frac{\sum\left(\frac{TP}{TP + FN}\right)}{n_{classes}} = \frac{0 + 1 + 1}{3} = 0.667\ (66.7\%)$$

The F1-Score is derived from the harmonic mean of the macro-averaged Precision and Recall:

$$F1\ Score = 2 \times \frac{Precision_{macro} \times Recall_{macro}}{Precision_{macro} + Recall_{macro}} = 2 \times \frac{0.667 \times 0.667}{0.667 + 0.667} = 0.667\ (66.7\%)$$

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Tabel 3. Multi-class Confusion Matrix Performance

Performance Metric	Small (35g)	Medium (70g)	Large (105g)	Macro-Average
Precision	0%	100%	100%	66.7%
Recall (Sensitivity)	0%	100%	100%	66.7%
F1-Score	-	100%	100%	66.7%

As detailed in **Table 3**, the system achieved a 100% overall classification accuracy regarding the targeted fuzzy rules. However, the macro-averaged Precision, Recall, and F1-Score recorded at 66.7%. This statistical phenomenon is strictly a consequence of an imbalanced dataset; because the test subjects were highly active, growing kittens, the system adaptively and correctly triggered only the 'Medium' and 'Large' portions. The 'Small' portion class lacked True Positive samples (0/0), which mathematically skewed the unweighted macro-average. Despite this, the absence of False Positives and False Negatives confirms the algorithm's flawless execution.

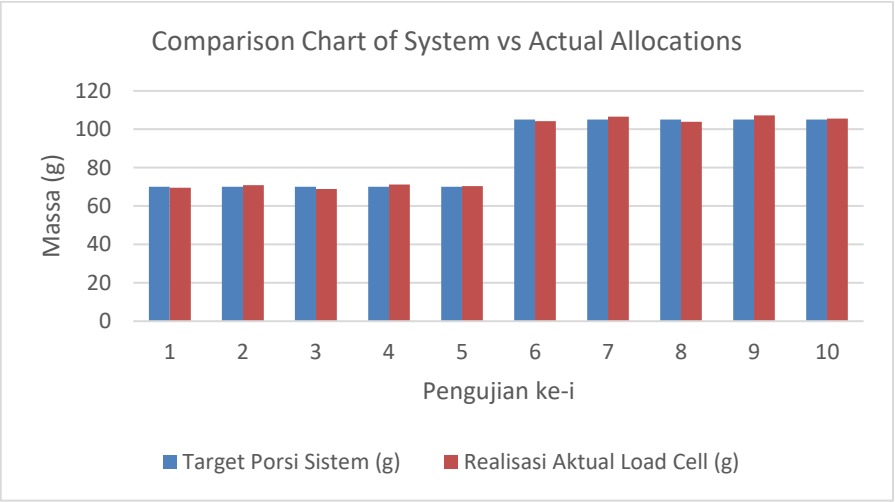


Figure 11. Comparison Chart of System vs Actual Allocations

As detailed in **Figure 11**, the physical realization of these calculated targets by the auger mechanism was analyzed . Comparing the target fuzzy output (e.g., 70g or 105g) against the actual mass dispensed and measured by Load Cell 2 revealed a minimal average error of 1.15% across dispensing trials. This equates to a 98.85% actuation accuracy, proving that the cyclic ON/ OFF motor control paired with the auger effectively prevents severe overshooting and dispenses highly accurate portions.

4. CONCLUSION

The design and implementation of the smart cat feeding system utilizing the NodeMCU ESP32 and the Sugeno Fuzzy Logic method within an IoT framework have been highly successful. The physical integration of load cells, ultrasonic monitoring, and an auger dispensing mechanism provided a robust foundation for precision pet care. Performance evaluations demonstrated exceptional sensor accuracy, with load cell measurements achieving an average accuracy exceeding 98.6% and the ultrasonic stock sensor reaching 99.15%. The system exhibited reliable IoT connectivity, maintaining punctuality with an 11.07 second average delay and demonstrating autonomous offline resilience. Crucially, the implementation of the zero-order Sugeno Fuzzy Logic algorithm on the microcontroller was flawlessly executed. The mathematical validation against MATLAB simulations resulted in

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zero computational error (MSE=0, RMSE=0, R^2=1), and the physical realization of these adaptive feed portions achieved a 98.85% accuracy. By intelligently adapting food portions based on age, weight, and activity level, this system effectively bridges the gap between rigorous nutritional guidelines and the practical constraints of modern pet owners.

Future research should involve long-term testing with a broader demographic of cats, particularly senior or obese subjects, to fully exercise the lower-bound fuzzy logic rules and evaluate longitudinal health impacts.

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism and represents original academic research.

7. AUTHORS' CONTRIBUTION/ROLE

Dennis Putra Dwiwangga: Conceptualization, Methodology, Hardware Assembly, Software Development (IoT and Fuzzy Logic), Data Collection, and Original Draft Preparation. Lilik Anifah**:** Formal Analysis, and Supervision.

8. DECLARATION OF THE USE GENERATIVE AI IN THE MANUSCRIPT PREPARATION PROCESS

Authors declare that did not use Generative AI in the manuscript preparation process upon submission of the paper.

REFERENCES

[1] Petfood Industry, "How cats stole Indonesia's pet food market," *PetfoodIndustry.com*, 2023, [Online]. Available: https://www.petfoodindustry.com/global-commerce/article/15745418/how-cats-stole-indonesias-pet-food-market

[2] Suara Jakarta, "Ancaman Baru di Tengah Kota Jakarta: Ledakan Populasi Kucing Liar," *Suara.com*, 2025, [Online]. Available: https://jakarta.suara.com/read/2025/09/16/203432/ancaman-baru-di-tengah-kota-jakarta-ledakan-populasi-kucing-liar

[3] ABC News, "Indonesian MPs' cats have become the unexpected symbol of protests," *ABC News Australia*, 2025, [Online]. Available: https://www.abc.net.au/news/2025-09-09/indonesia-protests-cat-politicians/105748582

[4] FEDIAF Nutritional Guidelines, "Nutritional Guidelines For Complete and Complementary Pet Food for Cats and Dogs," Sep. 2025.

[5] J. Wakshlag and J. Loftus, "Canine and feline obesity: a review of pathophysiology, epidemiology, and clinical management," *Veterinary Medicine: Research and Reports*, p. 49, Dec. 2014, doi: 10.2147/vmrr.s40868.

[6] A. W. Rollins and M. Murphy, "Nutritional assessment in the cat: Practical recommendations for better medical care," *J. Feline Med. Surg.*, vol. 21, no. 5, pp. 442–448, May 2019, doi: 10.1177/1098612X19843213.

[7] E. N. Bermingham, D. G. Thomas, P. J. Morris, and A. J. Hawthorne, "Meta-analysis:

Energy requirements of adult cats," *British Journal of Nutrition*, vol. 103, no. 8, pp. 1083–1093, Apr. 2021, doi: 10.1017/S000711450999290X.

[8] W. T. A. Bisri and I. Aprilia, "Rancang Bangun Alat Pemberi Pakan Otomatis Terhadap Kucing Peliharaan Menggunakan Arduino Uno," *TESLA: Jurnal Teknik Elektro*, vol. 23, no. 1, Mar. 2021.

[9] S. Serius Zendate and S. Sitohang, "Rancang Bangun Prototype Cat Feeder (Smart-Cat) Berbasis Iot," *JURNAL COMASIE*, vol. 10, no. 03, 2024.

[10] W. Aditya and S. Subektiningsih, "*Schedule Cat Feeder* Berbasis *Internet of Things* Menggunakan Wemos D1 Mini dan Telegram," *Jurnal Teknologi Informasi dan Ilmu Komputer*, vol. 11, no. 1, pp. 183–190, Feb. 2024, doi: 10.25126/jtiik.20241117847.

[11] H. Ngarianto and A. A. S. Gunawan, "Pengembangan Automatic Pet Feeder Mengunakan Platform Blynk Berbasis Mikrokontroller ESP8266," *Engineering, MAthematics and Computer Science (EMACS) Journal*, vol. 2, no. 1, pp. 35–40, Jan. 2020, doi: 10.21512/emacsjournal.v2i1.6260.

[12] M. Rayhan Arisma, A. Ahmad Dahlan, and P. Negeri Padang, "Design of a Microcontroller-Based Automatic Cat Feeding and Monitoring Device," *Journal on Internet Engineering Technologies and Applications*, vol. 1, no. 1, pp. 1–7, 2024.

[13] N. Wandi Al-Hafiz, "Design of an Internet of Things-Based automatic cat feeding control device (IoT)," *Jurnal Mandiri IT*, vol. 13, no. 1, pp. 161–169, 2024, [Online]. Available: www.ejournal.isha.or.id/index.php/Mandiri

[14] N. Awasthi, A. Dubey, N. Gupta, and H. Sharma, "Control Of Servo Motor By Ultrasonic Sensor Using Arduino Uno", [Online]. Available: www.irjmets.com

[15] M. A. Sadad, L. Nurpulaela, and R. Rahmadewi, "Analisis Metode Fuzzy Logic Pada Sistem Pemberi Makan Kucing Otomatis Studi Kasus Makanan Kering," *Jurnal Teknik Elektro dan Komputasi (ELKOM)*, vol. 5, no. 1, pp. 16–27, Mar. 2023, doi: 10.32528/elkom.v5i1.8544.

[16] M. A. Hidayat and S. Jayakrista, "Smart Pet Feeder on Cat Food Portions Using Mamdani's Fuzzy Logic Inference System Method," *Journal of Computer Engineering, Electronics and Information Technology*, vol. 2, no. 1, pp. 13–28, May 2023, doi: 10.17509/coelite.v2i1.56926.

[17] F. Iman, O. Anugrah, and A. Purnama, "Implementation Of An Arduino Uno-Based Automatic Cat Feeding Monitoring System Using The Fuzzy Logic Method Implementasi Sistem Monitoring Pemberian Pakan Kucing Secara Otomatis Berbasis Arduino Uno Menggunakan Metode Fuzzy Logic," *Journal of Scientech Research and Development*, vol. 7, no. 2, Dec. 2025.

[18] S. H. Khoiroh, M. Ridwan, and S. Maftukhah, "Penerapan Logika Fuzzy Pada Rancang Bangun Alat Pakan Kucing Otomatis dan Monitoring Sisa Pakan Dengan Aplikasi Blynk," Tangerang, Nov. 2022.

[19] U. Athiyah, A. P. Handayani, M. Y. Aldean, N. P. Putra, and R. Ramadhani, "Penerapan Metode Logika Fuzzy dalam Evaluasi Kinerja Dosen," *Journal of DINDA (Data Science, Information Technology, and Data Analytics)*, vol. 1, no. 2, Dec. 2021.

[20] R. Septiawan, N. Kn, and K. Kunci, "Uninterruptible Power Supply (Ups) Portabel Sebagai Cadangan Daya Berbasis Iot Pada Smart Home," 2023. doi: https://doi.org/10.35968/jti.v12i2.1117.

[21] A. Oktopryadin and A. Purnama, "IoT-Based UPS Device Electricity Usage Monitoring System with MQTT Protocol," 2025. [Online]. Available: http://jurnal.polibatam.ac.id/index.php/JAIC

[22] D. Nayanasiri and Y. Li, "Step-Down DC–DC Converters: An Overview and Outlook," Jun. 01, 2022, *MDPI*. doi: 10.3390/electronics11111693.

[23] S. Sibuea and B. Saftaji, "Perancangan Sistem Monitoring Beban Kendaraan Menggunakan Teknologi Sensor Load Cell," *Jurnal Teknologi Informatika dan Komputer*, vol. 6, no. 2, pp. 144–156, Sep. 2020, doi: 10.37012/jtik.v6i2.309.

[24] O. S. Al-Dahiree *et al.*, "Design and Shape Optimization of Strain Gauge Load Cell for Axial Force Measurement for Test Benches," *Sensors*, vol. 22, no. 19, Oct. 2022, doi: 10.3390/s22197508.

[25] L. Anifah, *Pattern Recognition*, 1st ed. Penerbit KBM Indonesia, 2025.

[26] X. T. Pham, M. T. Nguyen, C. K. Pham, and K. X. Thuc, "Buck Converter with Improved Efficiency and Wide Load Range Enabled by Negative Level Shifter and Low-Power Adaptive On-Time Controller," *Electronics (Switzerland)*, vol. 14, no. 12, Jun. 2025, doi: 10.3390/electronics14122425.

[27] L. C. Souza, L. de S. da C. e. Silva, F. J. M. de Seixas, and L. D. O. Arenas, "3SSC-A-Based Step-Down DC–DC Converters: Analysis, Design and Experimental Validation," *Energies (Basel).*, vol. 15, no. 20, Oct. 2022, doi: 10.3390/en15207710.

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