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Automatic Chicken Feeding Machine Using Fuzzy Inference System

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ABSTRACT

Efficient feed management is a crucial factor in increasing chicken farm productivity. However, manual feeding systems are often inconsistent and labor-intensive. To address these issues, this study designed and implemented an automatic chicken feeder equipped with a fuzzy inference system, where the fuzzy system plays a role in processing sensor data. The sensors used in this research are temperature sensors, ultrasonic, RTC, electric motors and microcontrollers. This system can automatically determine the timing and amount of feed given based on parameters such as time, number of chickens, and the level of remaining feed in the container. The fuzzy method is used because it can handle uncertain and variable input data and allows for more flexible decision-making. System testing was conducted using MATLAB simulations to test the fuzzy logic response to feed quantity and input conditions. In addition to simulation testing, hardware testing was also conducted to ensure that all physical components of the automatic chicken feeder functioned properly and directly according to the feed design. The simulation results showed that the defuzzifier value was 10, thus concluding that the motor movement of the device was categorized as moderate and also demonstrated that the system can provide feed in a timely and appropriate manner, while reducing feed waste. Thus, this tool has the potential to help farmers save time, operational costs, and improve feed efficiency.

1. INTRODUCTION

Poultry farming, particularly chicken farming, is a crucial sector in providing animal protein in Indonesia. Maintaining chicken productivity and health requires proper and regular feeding, which is crucial (Dayat, Jayanegara, and Sukria 2023). However, in practice, manual feeding is still often encountered. Feed consumption for chicks aged 1-7 days for feed consumption between 12-20 grams per day (Widodo et al. 2018), Meanwhile, for chickens aged 22-35 days, daily consumption is between 70-12 grams and for chickens aged 36-42 days, daily consumption per chicken is around 30-150 grams (Rasyaf 2012). Manual methods are not only labor intensive, In Indonesia, most of them still use a manual feeding system of around 70-80% because the livestock farming is still small-scale, but for developing countries such as Southeast Asia, Africa and Latin America, around 60-75% still use semi-manual methods, however, for large-scale livestock farming, they have switched to feed automation, especially in the commercial broiler sector (Birhanu et al. 2023). Irregularity in feeding schedule can have a negative impact on the growth and condition of chickens(Febry Rahmadhani Hasibuan, Putri Agustina Anggraini Arwira, Raini Dahriana Pulungan, Adyla Syukhraini Marwi, 2023), Apart from that, it can cause chickens to experience stress and have a low daily weight gain compared to those fed consistently, 15-20% experience slower growth compared to the controlled group of chickens (Widodo, W. & Kurniawan 2017). With the advancement of automation and artificial intelligence technology, many innovations have been developed to increase efficiency in the livestock sector. One such innovation is the use of automated feeding equipment

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(Setiawan, Desriyanti, and Vidyastari 2023). However, conventional automatic systems are often only based on scheduled times and do not take into account the actual condition of the chickens, such as the amount of remaining feed, the level of chicken activity or the environmental temperature (Fais 2025; Julfikar Diawan,Mustamin Hamid 2023). This research presents a new innovation: a fuzzy inference system with automatic control of feed timing and volume that can adjust feed based on parameters such as feed weight, chicken usage, and previous feed consumption. Unlike previous studies that only examined time or simple sensors, this system uses Mamdani fuzzy logic to improve feed distribution accuracy and feed consumption efficiency. This system also has the potential to be integrated with IoT platforms for real-time remote maintenance.

To overcome these limitations, a fuzzy inference system was established as part of intelligent control in chicken feeding (Sudarmawan, Panji Sasmito, and Primaswara 2021). Fuzzy Logic involves multiple inputs, outputs and indicates several types of data such as mathematical, experimental and numerical data (Okello et al. 2025). By utilizing input from various sensors such as feed weight, temperature and humidity sensors, the fuzzy inference system (FIS) can determine the optimal time and amount of feed automatically by adjusting to the actual conditions in the chicken coop (Otomatis 2024; Trinaldi 2022). FIS (Fuzzy inference system) is used to model and optimize process parameters (Mohammed et al. 2023). The main elements of a FIS system are fuzzification, inference and defuzzification (Samanta et al. 2022). Fuzzification is the process of converting precise inputs such as temperature and humidity into fuzzy values. These fuzzy values are then interpreted as degrees of membership in a fuzzy set based on a predetermined membership function. The result of fuzzification is a fuzzy value that belongs to one or more fuzzy sets, with degrees of membership indicated by values ranging from 0 to 1(Hendrawati et al. 2025). While defuzzification changes the fuzzy output produced by the inference system back to clear values that can be used as output for the control system(Vinayagam et al. 2023) By implementing an automatic feeding tool based on a fuzzy inference system, the feeding process is expected to be more efficient, scheduled on time, and optimally in accordance with the nutritional needs of chickens, so as to improve chicken welfare and overall livestock productivity.

This research aims to design and implement an automatic chicken feeding device that utilizes a fuzzy inference system, to increase feeding efficiency, reduce distribution delays, and adjust the amount of feed adaptively based on the chicken's needs which are influenced by parameters such as time, remaining feed weight and chicken age.

2. METHODS

The system architecture of the free-range chicken egg incubator consists of three stages, as shown in Figure 1.

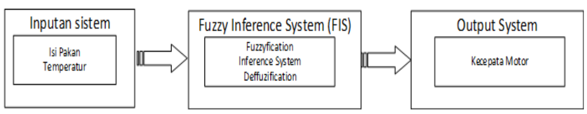


Figure 1. Architecture of the Automatic Chicken Feeder

A. System Input

The system analysis was conducted starting with an ultrasonic sensor used to detect the feed capacity in the container, as well as a temperature sensor that measures the air temperature around the device. Data obtained from these two sensors were then processed by an Arduino Uno microcontroller, which was then analyzed using a fuzzy inference system to determine the duration and rotation speed of the DC motor. In addition, an RTC (Real Time Clock) was used to automatically schedule chicken feeding, and system information was displayed on an LCD screen. In addition to hardware analysis, software analysis was also conducted to understand the software used in this project. Arduino IDE version 1.8.13 was chosen as the development environment because it supports Arduino Uno programming and provides various libraries needed in system design. This software is based on a combination of C++ and Java programming languages, which are considered suitable and compatible for the needs of implementing an automatic chicken feeding system based on fuzzy logic.

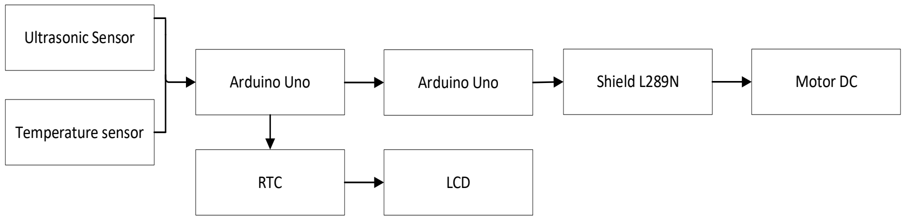


Figure 2. System block diagram

Figure 2 illustrates the working range of an automatic chicken feeding system based on fuzzy inference. This system is operated by ultrasonic and temperature sensors that detect environmental conditions and feed capacity. Data from both sensors are sent to an Arduino Uno microcontroller, which then uses fuzzy logic to interpret the data and determine feeding decisions. The results of the fuzzy logic analysis are then sent to the L298N drive motor, which controls the DC motor to activate the feeding mechanism. On the other hand, a Real Time Clock (RTC) module is used to automatically adjust the feeding time based on the clock, and an LCD screen displays system information in real time. In addition to the block diagram, this journal also features a flowchart that explains how the fuzzy application works to determine the time duration of the feeding motor rotation speed, as shown in Figure 3.

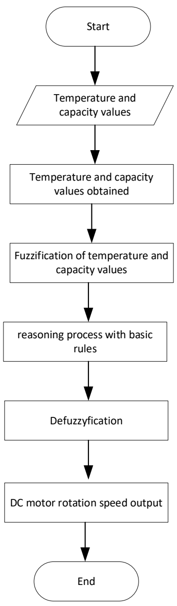


Figure 3 overall system flowchart

Figure 3 illustrates the level of work performed by a fuzzy inference system in an automated poultry production process. Temperature and feed capacity data are collected using installed sensors. Once the data is collected, a fuzzy process is performed on the accuracy and capacity values, which involves converting the numerical values into fuzzy inputs. The next step is fuzzy regression (fuzzy inference), which uses predefined rules of thumb to determine the outcome based on a combination of sample size and probability. The inference results are then processed through a defuzzification step, which involves converting the fuzzy kernel into a tautological value (crisp output). This value is used to determine the speed of the DC motor as the system output, which directly affects the quantity and speed of electricity consumption. This process ends after the output is complete.

B. Fuzzy Inference System (FIS)

Fuzzy Inference System can be used as a prediction model when the input and output are uncertain, whereas using classical methods such as regression techniques cannot model uncertainty well (Seidi, Yaghoubi, and Shirazi 2025), Therefore, the FIS method is very suitable for use in automatic chicken feeding systems. Fuzzy control regulates the input-output relationship (Julfikar Diawan,Mustamin Hamid 2023). The main process that controls the automatic chicken feeding system consists of Fuzzification, Fuzzy inference system and Defuzzification which sequentially function to change the input into a fuzzy set, then processed using fuzzy rules to produce output in the form of a firm value to regulate the work of the actuator (Hendrawati et al. 2025),(Barzegar et al. 2024)(Salameh et al. 2025). FIS using the Mamdani method consists of three main steps:

1. Fuzzifcation: In this stage, the clear input is converted into fuzzy input known as linguistic variables through different membership functions. (Barzegar et al. 2024)(Khan et al. 2025). Membership functions Membership functions are graphical representations that quantify linguistic terms and represent fuzzy sets graphically. Common membership functions include triangular, Gaussian, trapezoidal, and bell-shaped

(Rajaprakash et al. 2025). Fuzzification assigns numeric input values to membership levels in fuzzy sets based on text. In this study, we use the Trapezoidal membership function, which provides a smooth transition between different membership degrees, which helps in capturing uncertainty more accurately and more flexibly than other membership functions, and is suitable for various fuzzy logic applications (Barzegar et al. 2024). The following are the defuzzification results from the research on automatic chicken feeding equipment.

2. Rule Evaluation and Rule Aggregation: The inference engine uses the fuzzy rules of the knowledge base to generate fuzzy output. However, this output cannot be directly used in the process or system, therefore, it must be transformed into a clear output. Fuzzy rules are expressed as IF-THEN statements, after defining all IF-THEN rules, an aggregation process is applied to combine them, resulting in a single fuzzy set (Barzegar et al. 2024).
3. Defuzzification is a process of fuzzy inference system, which aims to convert fuzzy results (also known as linguistic or classification degrees) into clear output. This is necessary so that the system can analyze actuators or physical components, such as DC motors, accurately and clearly. Defuzzifiers come in various types, including Mean Of Maximum (MOM), Centroid Of Area (COA), Largest Of Maximum (LOM), Bisector of Area (BOA) and Smallest Of Maximum (SOM)(Barzegar et al. 2024)(Kamga et al. 2025)(Kusumadewi et al. 2025). Among these methods, the COA method is the most common method that we use in this study.(Barzegar et al. 2024).

Table 1 shows the variables used to define the membership function for the model used in the design of the automatic chicken feeding machine.

3. RESULT AND DISCUSSION

Testing was carried out with the aim of finding out whether the entire tool can work well or not and the fuzzy logic that has been implemented in the Arduino program can determine the duration of the motor speed on the chicken feeding tool.

1. Fuzzifikasi of Input and output Variables

Fuzzification is used to convert clear input criteria into degrees of membership in a predefined fuzzy set (Jalalifar, Delavar, and Ghaderi 2025).

Table 1. Linguistic terms and numerical terms for input

Linguistic Term	Numerical Term	Linguistic Term	Numerical Term
Feed Content		Temperature	
Little	≤ 5cm	Cold	≤ 37 ^{0}C
Medium	>5 cm dan ≤ 7cm	Medium	>37 ^{0}C dan ≤ 39^{0}C
Lots	> 7	Hot	>39 ^{0}C

c. Automatic Chicken Feeding Machine Design

The design of this automatic chicken feeder uses a fuzzy inference method to intelligently regulate the amount and time of feeding, taking into account input variables such as the number of chickens, feeding time, and remaining feed in the container, so that the system can operate flexibly and efficiently according to real conditions in the field.

Figure 4. Automatic Chicken Feeding Machine Design

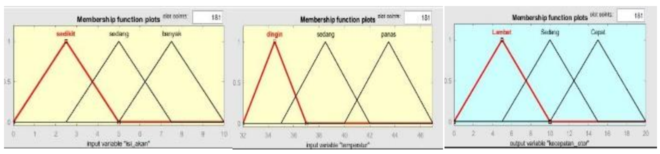


Figure 5. Membership Function plot of input (feed content, temperature) and output (motor speed)

2. Rule Evaluation and Rule Aggregation

The rule base in the fuzzy inference system is designed based on if-then logic, which regulates the relationship between input variables such as the number of chickens, remaining feed, and time, to determine the output in the form of the amount of feed to be given. The following is the simulation result using Matlab.

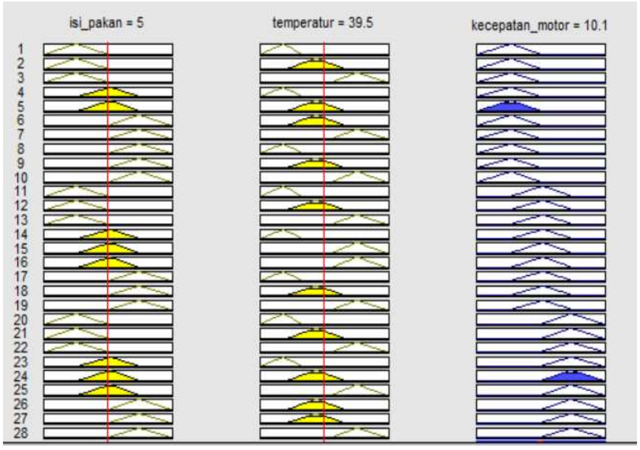


Figure 6. MATLAB Rule Viewer output

Based on the rule viewer shown in Figure 6, it explains that the fuzzy inference system receives two input parameters, namely a feed content of 5 cm and an environmental temperature of 39.5°C. In the fuzzification stage, the feed content value of 5 cm is included in the Low and Medium categories with overlapping membership degrees, while the temperature of 39.5°C is completely in the Hot category. The fuzzy inference process then activates a number of relevant rules based on the combination of these inputs. These rules produce a fuzzy output in the form of a DC motor speed level which is then converted into a crisp value through the defuzzification process. The defuzzification results show that the system recommends a DC motor speed of 10.1, which indicates that the motor will rotate at a medium to high speed. This reflects the system's adaptive response to hot temperature conditions—which physiologically increase the activity and feeding needs of chickens—and the decreasing feed volume, so that faster and more efficient feed distribution is needed.

3. Defuzzifikasi

a. Test Analysis Results

This test was conducted comprehensively to determine the results of the fuzzy logic application to determine whether the speed duration can run properly. The test results are displayed in Table 1.

Table 2. Temperature Measurement Data

Test data	Sensor measurement data	
	Capacity data	Temperature data
1	9 cm	36,81
2	8 cm	36,95
3	6 cm	36,84
4	4 cm	36,73
5	3 cm	37,16

Table 1 above is the test data for the capacity and temperature values from two different sensor inputs which were taken 5 times as an example for modeling tools using Mamdani fuzzy logic.

b. Metode Centroid Of Area (COA)

At this stage, the reasoning function of the obtained data is tested using fuzzy logic. The calculation uses sample number 1 as a reference. The first data in the table yields a capacity value of 9 cm, with the following membership values.

- Low membership ≤ 5

$$\mu\, Low\ (\leq 5) = \begin{cases} \dfrac{9-5}{5-2{,}5} \end{cases} = \frac{4}{2{,}5} = 1{,}6$$

- Membership is in progress > 5 cm and ≤ 7

$$\mu\, Medium\ (> 5\ cm\ dan\ \leq 7\ cm) = \begin{cases} \frac{9-2{,}5}{5-2{,}5} \end{cases} = \frac{6{,}5}{2{,}5} = 2{,}6$$

- Multiple memberships > 7

$$\mu\, Lots\ (> 7\ cm) = \begin{cases} \dfrac{9-7{,}5}{7{,}5-5} \end{cases} = \frac{1{,}5}{2{,}5} = 0{,}6$$

Next is to find the second membership value, namely the temperature, which is obtained as a temperature value of 36 with the following membership values.

- Cold temperature membership 36 ≤ 37

$$\mu\, Cold\ \ 36{,}81 \leq= \begin{cases} \dfrac{37-36{,}81}{37-35} \end{cases} = \frac{0{,}19}{2} = 0.095$$

- Moderate temperature membership 35 ≥ 36 ≤ 39

$$\mu\, Medium\ 35 \geq 36{,}81\ \leq 39 = \begin{cases} \dfrac{36{,}81 - 35}{39 - 35} \end{cases}$$
$$= \frac{1{,}81}{4} = 0{,}452$$

- Hot temperature membership 36 $\leq$ 40

$$\mu\, panas\ 36{,}81\ \leq 40 = \begin{cases} \dfrac{40 - 36{,}81}{44 - 40} \end{cases} = \frac{1{,}5}{4}$$
$$= 0{,}375$$

The value of the capacity and temperature status is for capacity [1.6,4 and 0.6] and for the value of temperature is [0.095, 0.452, 0.375] while for the predetermined rule value is [4.5, 10, 14.5] then for the PWM change process is:

$$Z = \frac{(1{,}6 * 4{,}5) + (2{,}6 * 10) + (0{,}6 * 14{,}5)}{1{,}6 + 2{,}6 + 0{,}6}$$
$$= \frac{41{,}9}{4{,}8} = 8{,}72$$

The sum of the capacity values above yields a value of 8.72. The capacity yields a value of 11.26, as formulated below.

$$Z = \frac{(0{,}095 * 4{,}5) + (0{,}452 * 10) + (0{,}375 * 14{,}5)}{0{,}095 + 0{,}452 + 0{,}375}$$
$$= \frac{10{,}385}{0{,}922} = 11{,}26$$

From the results of the PWM changes, the figures show 9.01 and 11.26 for the defuzzification values of the two sensors, namely the capacity sensor and the temperature sensor. The RPM measurement of the motor is carried out to check the relationship between the PWM value received and the actual reaction of the motor in the form of rotational speed, so that the system can be tested quantitatively. All data from the analysis table is tested in the same way as the first data test. The fuzzification results from the analysis table are displayed in the following table:

Table 3. Fuzzy Test Results

No	Capacity Data	Temperature	Data Set	a	z	a-z
1	9 cm	36, 81	many, moderate	0,1	19	0,2
2	8 cm	36, 95	many, moderate	0,4	18	0,3
3	6 cm	36, 84	moderate, moderate	0, 2	18	0,2
4	4 cm	36, 73	few, moderate	0,1	25	0,1
5	3 cm	37, 16	few, moderate	01	25	0,1
∑α.p				0, 9	∑α-p*z	0,9

From the test results data in Table 4.2, the minimum value of α-predicate and z for each rule is obtained. The next step is to find the output value in the form of crips (z). The method used in this process is the Center Average Defuzzifier. The method is written in the equation.

$$Z = \frac{\sum(\alpha\, \rho i * Zi)}{\Sigma\, (\alpha\, \rho i)}$$

Information :

Z = Centered average defuzzification

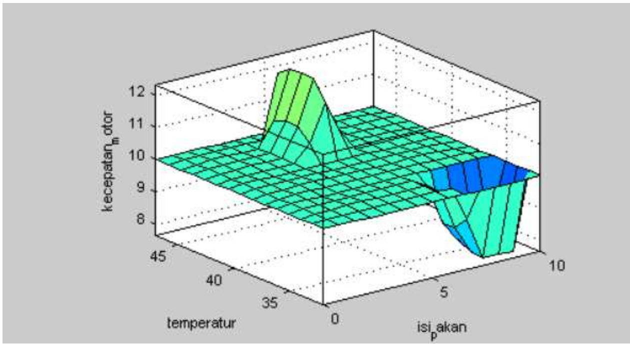
α_p = Predicate alpha value (minimum value of membership degree)

Zi = crisp value obtained from inference results

I = Number of fuzzy rules

The next is the defuzzification calculation process using the Center Average Defuzzifier method.

$$Z = \frac{\sum(\alpha\, \rho i * Zi)}{\Sigma\, (\alpha\, \rho i)} = \frac{0{,}9 * 9{,}0}{0{,}9} = 10$$



Gambar 7. Urface View Mamdani FIS

Figure 7 shows a three-dimensional surface representing the influence of environmental temperature and feed content variables on the rotational speed of the DC motor as a feed dispensing actuator. Based on the simulation results: When the feed content in the container is at a low level (0–2 cm) and the environmental temperature is high (40–45°C), the system responds by increasing the DC motor speed to near the maximum value (around 12). This aims to accelerate the feeding process so that the chickens' nutritional needs can be immediately met in temperature conditions that have the potential to increase the chickens' metabolic activity. Conversely, when the feed content is still high (8–10 cm), even though the temperature increases, the system regulates the motor speed to a minimum value (around 8), because the feed availability is considered still sufficient so that additional supplies are not needed in the near future. At medium to low temperatures (35–39°C), the system maintains the motor speed at an intermediate value (9–10), indicating stability in the feed distribution process that is not affected by extreme temperature changes. Based on these results, it can be concluded that the fuzzy inference system successfully regulates the feeding speed automatically and adaptively according to environmental conditions and available feed capacity, thereby increasing the efficiency and accuracy of feeding in the poultry farming system. So the PWM value obtained from the data can be categorized into the medium fuzzy output range with the following provisions:

Table 4. Range Output Fuzzy

No	Terms	Range
1	Slow	0 < = z < 5
2	Medium	5 < = z < 10
3	Fast	10 < = z < 20

4. CONCLUSION

Based on the test results that have been carried out on the application of fuzzy to determine the speed of DC motor movement in an automatic chicken feeder, it can be concluded:

1. The addition of fuzzy logic to this automatic chicken feeder system has been realized and can work well to determine the speed of motor rotation so that it is not excessive or lacking when feeding.
2. To drive the DC motor, a PWM with a duty cycle of more than 30% is needed so that calculations are needed to determine the minimum OCR2 value so that the motor can move.
3. The use of temperature sensors on the tool is considered less effective because the placement of the tool can change according to the wishes of the farmer.
4. The travel time required for the conveyor to distribute chicken feed depends on the amount of feed available. The more feed there is, the longer the travel time required.

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