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Smart Shrimp Farming Using Internet of Things (IoT) and Fuzzy Logic

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***Abstract* -** In the case of ponds with Litopenaeus Vannamei shrimp, water quality parameters play a significant role in shrimp growth. Leveraging technology enhances water quality to optimize growth and survivability in the shrimp farming industry. The research aimed to empower local farmers with smart shrimp farming technologies, including Information Technology (IT), such as the Internet of Things (IoT), and Fuzzy Logic. The research also involved a comparison between Litopenaeus Vannamei shrimp in two different aquariums: one serving as a control group and the other implementing IoT and Fuzzy Logic for a period of 30 days. The initial Litopenaeus Vannamei shrimp stocking was 135 shrimps for control aquariums and 132 for experimental aquariums. Then, the research used Arduino ESP 8266, Raspberry Pi 3, and SciKit-Fuzzy library to record and process the data. Through the application of IoT and Fuzzy Logic, the research successfully increases survivability by 6%, specific growth rate by 28%, and length by 8% in 30 days compared to conventional methods. The results highlight the potential use of technology in Litopenaeus Vannamei shrimp farming. The proposed system's hardware and software architecture can be easily scaled to accommodate the needs of Litopenaeus Vannamei shrimp farmers with multiple ponds, offering flexibility and adaptability.

Keywords: smart shrimp farming, Internet of Things (IoT), Fuzzy Logic

I. INTRODUCTION

Shrimp cultivation is one of the most popular aquaculture sectors among the people in Indonesia. Shrimp cultivation in 2019 contributed 36,27% of the total value of fishery exports in Indonesia. Shrimp export volume was recorded at 197,43 thousand tons in 2018 and 517,39 thousand tons in 2019. Then, it is predicted that in 2024, shrimp aquaculture production will reach 1.290 thousand tons (Balai Perikanan Budidaya Air Payau Situbondo, 2021). However, many traditional shrimp farmers still do not pay attention to water quality or use complete equipment to monitor water quality (Sukaridhoto et al., 2017). Traditional farmers still predict water quality based on shrimp behavior during rearing.

In terms of water quality, many parameters can affect the growth and development of shrimp, such as but not limited to temperature, Dissolved Oxygen (DO), and Potential of Hydrogen (pH). According to Venkateswarlu et al. (2019), the best water temperature is at 24,47 °C, with a DO value of 5,37 mg/L and pH value of 7,67. Then, it is also believed that these parameters will also fluctuate and can have a negative impact on shrimp growth and development if these parameters are outside the tolerance limit of the shrimp (Sukaridhoto et al., 2017).

Internet of Things (IoT) and Fuzzy Logic can be a solution to maintain water quality in shrimp ponds in Indonesia. By using IoT, monitoring and controlling can be done automatically and remotely through the Internet in real time (Herman et al., 2019). On the other hand, the Fuzzy Logic method adopts human judgment on a truth, which is expressed in a continuous function from 0 to 1. In contrast to classical logic, which states everything is true or false or yes or no (Utama et al., 2020). Combining these two technologies is expected to optimize pond water quality automatically and independently of human decisions.

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Several previous studies have conducted research in the field of IoT and Fuzzy Logic. Fuzzy Logic is implemented to generate true random numbers and routing networks (Kumar & Saminadan, 2019; Tatas & Chrysostomou, 2017). Moreover, IoT and Fuzzy Logic are adopted on smart home gateways to calculate decisions for emergency vehicles (Firouzi et al., 2020; Rout et al., 2020). These four previous studies show that Fuzzy Logic can improve the previous system, such as faster and more accurate decision-making, low-level intelligence, and scalability in the proposed system. In the field of aquaculture, Fuzzy Logic classifies air quality based on sensors installed on IoT (Shandikri & Erfianto, 2021; Bokingkito Jr & Caparida, 2018; Agustianto et al., 2021). It sends information to farmers so that farmers can make decisions more quickly and accurately.

Moreover, previous research on smart shrimp farming has automated the inspection of water quality parameters in ponds. The goal is to develop a smart aquaculture monitoring system that can automate the inspection of water quality parameters, such as pH, DO, and temperature, in real time. The system is tested at an actual site located at Fisheries Research Institute (FRI), Gelang Patah, Johor. It can provide reliable and accurate data when compared to commercial devices used (Abdullah et al., 2021). Previous research is different from the current research that utilizes Arduino ESP 8266 to collect data and to be an actuator. Arduino is programmed as a JavaScript Object Notation (JSON) Web Server. Then, Raspberry Pi 3 can call a web server to retrieve sensor data or to command the actuator. Such an approach can help horizontal scalability with ease and lower cost as shrimp farms tend to utilize numerous ponds.

In the research, Arduino is used as a tool to read and measure water quality parameters, such as temperature, pH, and DO in water. The device used for reading and measuring is Arduino Uno with built-in ESP8266. This device can also be connected to a wireless router and function as a JSON Web Server. Then, the Raspberry Pi 3 calls the Arduino web server, which will read the parameter data and supply it to the Fuzzy Logic model. Next, the model will call the actuator, which will run the heater, aerator, and buffer solution according to the results of the Fuzzy Logic model.

Referring to Atmaja et al. (2018), the use of heaters is positively correlated with increasing water temperature. Meanwhile, the previous research concludes that the use of aerators can also be positively correlated with increasing the DO value in the water (Yuswantoro et al., 2018). According to De Araújo et al. (2020), Calcium Carbonate ($CaCO3$) water can be used to increase the pH of pond water, which is safe for shrimp. Next, it is revealed that there is a correlation between the use of aerators and the pond water temperature (Abdelrahman & Boyd, 2018). The use of an aerator can reduce the temperature of the water in the pond. The higher the temperature is, the minimum DO before mass mortality in shrimp also increases.

The primary goal of the research is to leverage IoT and Fuzzy Logic to enhance and maintain optimal water quality in shrimp ponds, thereby maximizing shrimp growth, development, and survivability for farmers. The research benefits can be a foundation for introducing technological advancements in aquatic aquaculture, with a particular focus on shrimp farming. The research aims to increase the survivability, length, and weight of cultured shrimp while improving the overall efficiency of the industry.

II. METHODS

The research begins with a literature study on shrimp farming and IoT architecture and what logic is used when the sensor triggers an anomaly that is outside the standard. The researchers use several journals as a reference for how to cultivate shrimp. For example, Tacon et al. (2013) provided information on shrimp feeding standards. Then, several other journals, such as Durai et al. (2021), Venkateswarlu et al. (2019), Chakravarty et al. (2016), De Araújo et al. (2020), and Ni et al. (2018), summarize water quality parameter standards for shrimp farming. From these standard parameters, the rules are used for Fuzzy Logic.

There are many approaches for architecture and actuators in IoT. The book by Rusli (2017) is used as a basis for designing Fuzzy Logic in the system created. After the architectural design is complete, the microcontroller is programmed. Then, Fuzzy Logic is implemented, and the actuators are configured. Next, a System Integration Testing (SIT) is carried out to ensure the design has gone well. To try the system, the researchers use an empty aquarium, which is filled with water and controlled by the system to achieve the target water quality parameters set on Fuzzy Logic. If the water quality can achieve the target and the system can maintain the water condition, the SIT is considered successful.

Next, there are two aquariums, one for research and one for control. The aquariums are filled with Litopenaeus Vannamei shrimp. The aquarium for research applies a system that has been developed, while the control aquarium is only limited to water quality parameter standards. Several shrimps are taken as samples at the shrimp stocking stage to measure the weight at stocking. Then, each aquarium is stocked with 135 shrimps for control aquarium and 132 shrimps for experimental aquarium as the initial population. This cultivation lasts for 30 days. The last stage is to evaluate the development of shrimp in both aquariums (research and control). On the thirtieth day, the shrimps' number populations, weight, and length are measured to evaluate the experiment and control aquariums' performance. The research stages can be seen in Figure 1.

For the details, the aquariums have a length of 60 cm, a width of 30 cm, and a height of 35 cm. Both aquariums are filled with seawater to a height of 30 cm. The initial stocking in both aquariums is 135 shrimps for the control aquariums and 132 shrimps for the experiment aquarium. These shrimps are cultivated for 30 days. The feed given in this experiment is a composition of 35% protein and 8% lipid diet with the following feeding in Table 1 (Tacon et al., 2013). The average initial weight at stocking is 0,18 g. For the research, shrimps are given 2,43 g of feed every 3,5 hours, following Table 1 of feeding rate and interval.

At the beginning and the end of the research, the initial and final population of Litopenaeus Vannamei are recorded to calculate the percentage of its survivability (%SR). The higher the percentage is, the better the performance of the tub will be. Equation (1) calculates the survivability (Sharawy et al., 2022). It has *%SR* as the survivability percentage, *Fn* as the final number of juvenile shrimps, and *In* as the initial number of juvenile shrimps.

$$\%SR = \frac{Fn}{In} \times 100 \quad (1)$$

At the beginning of the shrimp stocking, ten samples are taken randomly, and the weight of the shrimp's body is measured. After 30 days of cultivation, the weight of the shrimp will be measured again by sampling 10 shrimps for each research and control aquarium. Specific Growth Rate (SGR) calculates the difference between the initial and final weight of the shrimps divided by the number of days of cultivation. The higher the SGR is, the more the shrimp will grow. Equation (2) calculates SGR (Sharawy et al., 2020). *FBW* as final body weight, *IBW* as initial body weight, and *T* as time in days.

$$SGR = \frac{FBW - IBW}{t} x\, 100 \quad (2)$$

Next, Length Growth (Pm) calculates shrimps' length growth. It calculates the difference between the initial length at the time of stocking and the length at the end of the research. The greater the length is, the more the shrimps will grow (Manurung et al., 2018). It is shown in Equation (3). It includes *Pm* as the mean length of shrimp (mm), *Pt* as the average length

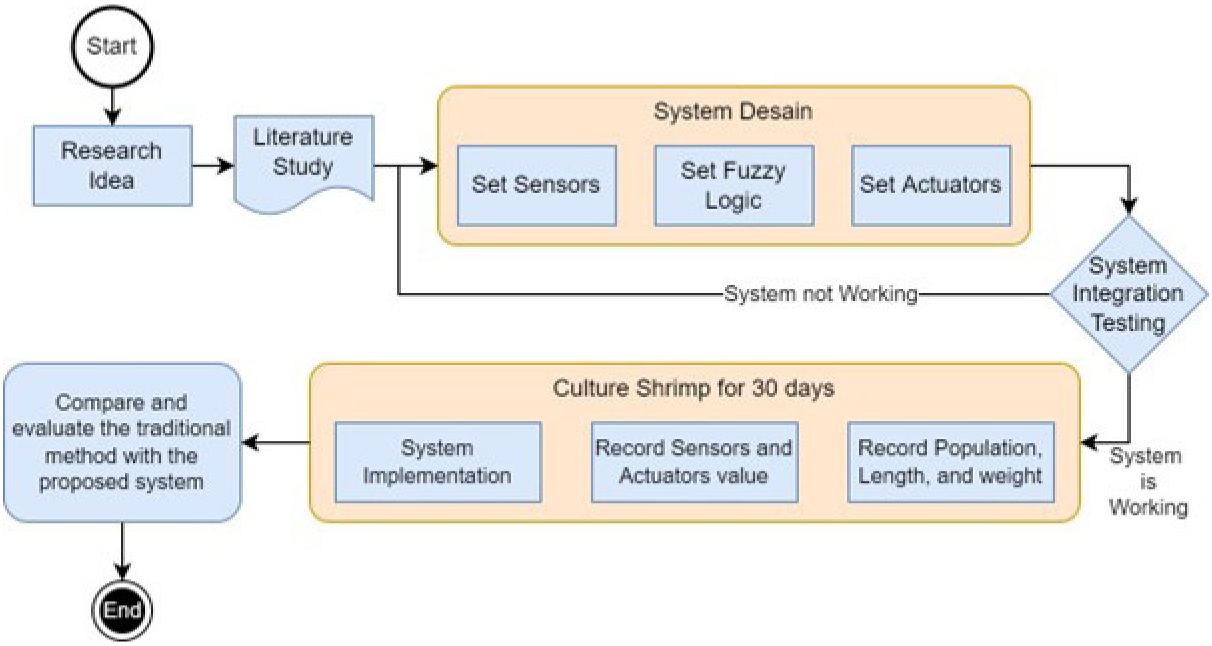

Figure 1 Research Stages Diagram

Table 1 Feeding Reference to Feed Shrimps for the Research (Tacon et al., 2013)

Average Body Weight (ABW) (g)	Feeding Rate (%)	Estimation Survival (%)	Interval Feeding (Hour)
< 1	10,0	100	3,5
1–3	8,0	98	3,5
3–5	6,0	96	3,5
5–7	5,0	94	2
7–9	4,0	92	2

of shrimp at the end of the research (mm), and *P0* as the average length of shrimp at the beginning of the research (mm).

$$Pm = Pt - P0 \tag{3}$$

The research also reads and measures water quality during the cultivation of Litopenaeus Vannamei shrimp. The parameters recorded are as follows: temperature, pH, and DO. Table 2 explains the importance of these parameters during cultivation. It is adopted from Venkateswarlu et al. (2019).

Table 2 Water Quality Parameters Scope in the Research and Their Importance for Shrimps.

Parameters	**The Importance of Parameters in Litopenaeus Vannamei Cultivation**
Temperature	Influencing photosynthesis in water, physiological responses of culture organisms, and decomposition of organic matter.
Potential of Hydrogen (pH)	Being a vital environmental characteristic as it affects the metabolism and other physical aspects of shrimps.
Dissolved Oxygen (DO)	Having a direct effect on feed consumption and affecting solubility and availability of nutrients in pond water.

Based on previous research in Table 3, it is evident that water quality parameters play a pivotal role in the development of Litopenaeus Vannamei Shrimps. Temperature, DO, and pH are identified as the most influential factors affecting the well-being of these shrimps, influencing their growth, and survivability. As a result, the research places significant emphasis on these key parameters. The researchers aim to monitor and enhance water quality by implementing an innovative approach that combines the power of IoT technology with Fuzzy Logic algorithms. This integration will provide real-time data and decision-making capabilities to maintain and optimize the ideal conditions for Litopenaeus Vannamei shrimps, ultimately ensuring their growth and survivability.

The water in the experiment aquarium is sampled by the microcontroller sensor. Raspberry Pi 3 reads the microcontroller using Python, which is called Arduino's Internet Protocol (IP) address. Then, it processes the data into Fuzzy Logic. Based on the results of the Fuzzy Logic, the Raspberry Pi 3 instructs the actuator microcontroller so that the water parameters will adjust to the standard that has been set. The sensor data that is read and the Fuzzy Logic results are uploaded to the Oracle Apex database. Then, these data can be consumed by mobile devices or computers, as shown in Figure 2. By using this template, horizontal scalability can be achieved easily by addressing each Arduino with their respective IP addresses.

The device for measuring and recording water quality is Arduino Uno Built-in ESP8266. Arduino is connected to a local area network with a 2.4 GHz 802.11 Wi-Fi network. Then, all the sensors connect to the Arduino Uno Built-in ESP8266 board using data and analog pins. Arduino Uno Built-in ESP8266 functions as a JSON Web Server where the sensor reading output can be viewed using the HTTP GET method at its IP address. Then, Raspberry Pi 3 runs a Python script that reads the IP address and sends the data to the Oracle Database in AWS using CxOracle. At the same time, the readings go through fuzzification, and Fuzzy Logic begins. Simpful library used for the research is the Mamdani FIS method (Spolaor, 2020). Arduino operates the heater and aerator, and the peristaltic pump runs on JSON Webserver. Fuzzy Logic output can be stored using HTTP GET on Arduino Actuator. After the value has been set, the water quality will change and improve. This loop will repeat after 2,5 minutes. The data flow can be described in Figure 3.

Table 3 Water Quality Parameters for Creating Fuzzy Membership and the Aggregated Value Using Average

Researchers	**Temperature (°C)**		**Dissolved Oxygen (DO) (mg/L)**		**Potential of Hydrogen (pH)**	
	Min.	**Max.**	**Min.**	**Max.**	**Min.**	**Max.**
Durai et al. (2021)	28,0	32,0	4,99	-	7,5	8,5
Venkateswarlu et al. (2019)	24,47	28,62	5,37	6,16	7,67	7,88
Chakravarty et al. (2016)	26,5	28,0	4,4	8,6	6,95	8,38
De Araújo et al. (2020)	28,0	32,0	5,0	9,0	7,5	8,5
Ni et al. (2018)	22,15	36,73	6,66	13,83	7,85	9,46
Average	**25,82**	**31,34**	**5,28**	**9,40**	**7,49**	**8,56**

For the temperature sensor, the DS18B203 sensor is used. This sensor has three pins: Voltage at Common Connector (VCC), Ground, and Data. The data pin is connected to VCC using a 4,7 kΩ resistor as the pull-down resistor. Then, the DS18B203 sensor can measure temperature from -50°C up to 125°C with an accuracy of 0,1°. For pH, a PH-4502C sensor is used. This sensor reads pH value of the liquid with an analog signal between 0 v to 5 v. Three buffer solutions have been prepared with pH of 4,01(25°C), pH of 7,01(25°C), and pH of 10,01(25°C) to calibrate PH-4502C sensor. From each buffer solution, a voltage measurement is recorded ten times each. Next, using the Sklearn library in Jupyter, a Linear Model is made using Linear Regression using measured voltage and pH. From the Linear Regression model, the researchers gain the formula as follows: $pH = -5{,}546 * V + 22{,}222$. This formula is applied to Arduino for measuring pH (Rozie et al., 2020).

The DO sensor used is SEN0237 DFRobot. This sensor reads the oxygen content in the liquid and sends an analog signal that the Arduino pins can read. This sensor uses a Galvanic Probe and has a detection range from 0 mg/L to 20 mg/L (DFRobot, n.d.). All sensors have a voltage-VCC of 5 volts. Then, a capacitor with 1000 µF is used for smoothing the supplied voltage. The temperature sensor is connected to the Digital Pin 2. The pH sensor is connected to Analog Pin 1, and the DO sensor is connected to Analog Pin 2. The following diagram in Figure 4 shows the relationship between the sensor and Arduino.

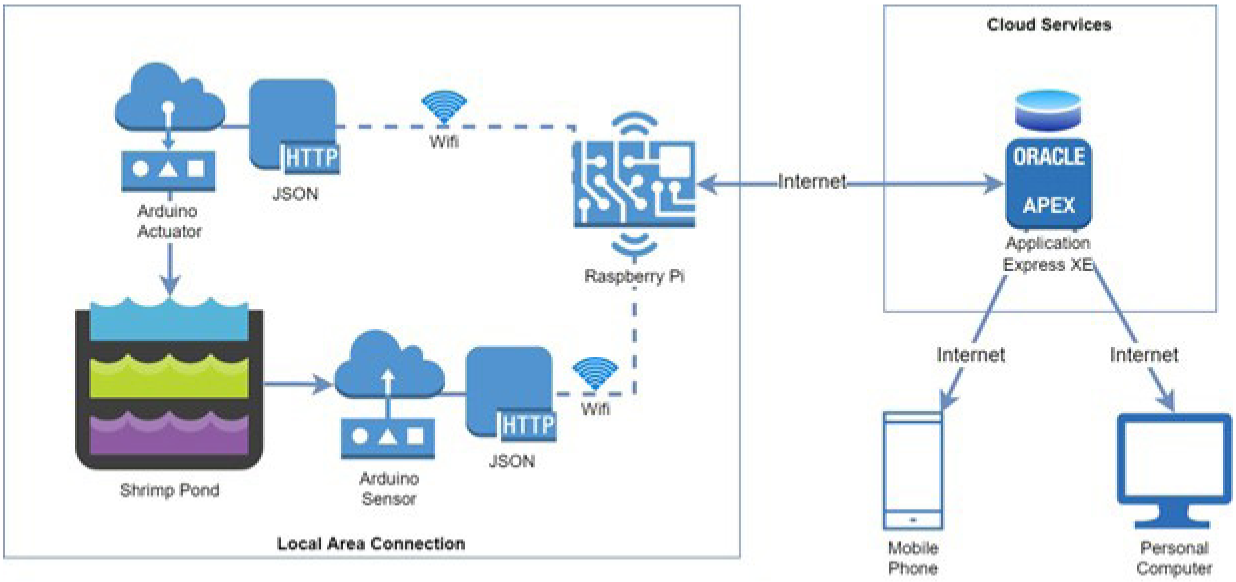

Figure 2 Proposed Design Architecture System

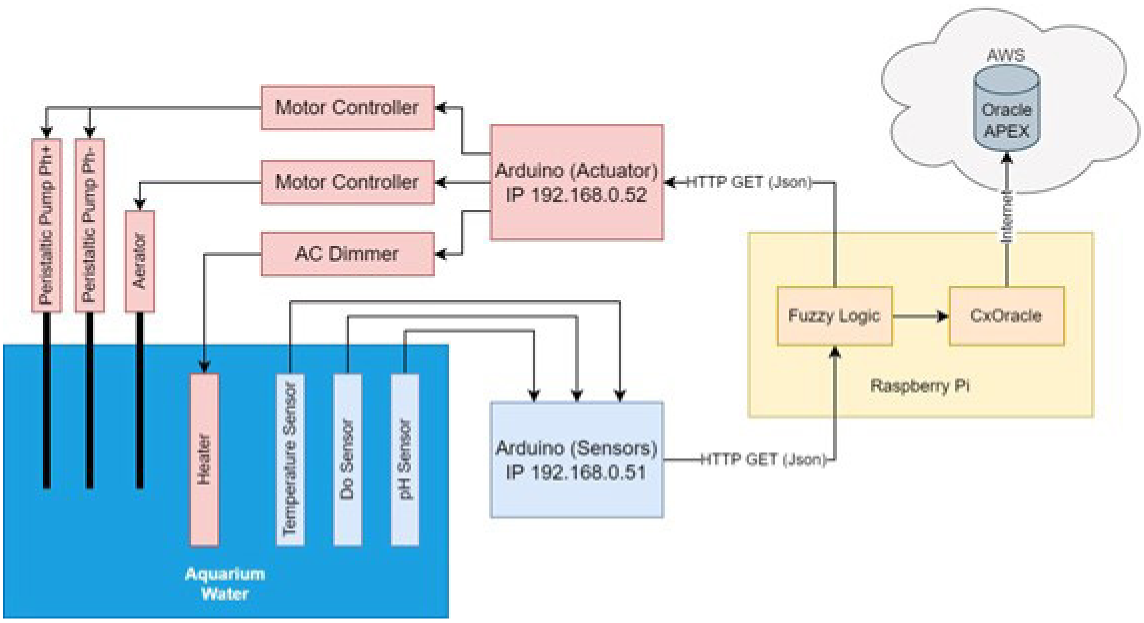

Figure 3 Block Diagram of Proposed System and Monitoring

The board that controls the actuator also uses the Arduino Uno Built-in ESP8266. JSON Web Server is also used to control the installed actuator. After the Fuzzy Logic has been calculated successfully, the Fuzzy Logic output will call the actuator using the JSON Web Server and provide the value. The Arduino Uno Built-in ESP8266 board accepts this value and runs a command to set the amount of current in the called actuator. For actuator aerators and peristaltic pumps, a voltage of 12v is required to drive the motor. Then, the speed of the aerator and peristaltic pump can be controlled by using the motor driver. Then, the motor driver gets a Pulse Width Modulation (PWM) signal from Arduino to determine the speed of the Actuator. Next, the heater is connected to the Alternating Current (AC) dimmer, which regulates the AC that enters the heater. The Fuzzy Logic output can have a value from 0 to 100, where 0 will turn off the heater, and 100 will turn on the heater with maximum current. Figure 5 shows a schematic of the pin addressed to motor drivers and AC dimmers.

Similarly, Fuzzy Logic is used to control water quality. First, the data from the sensor are processed with fuzzification. At this stage, the data from each sensor are classified into a degree of membership. Then, the previously created rule matches the membership results to produce Fuzzy output data. This output is processed into an output value that the actuator can read. This stage is called defuzzification (Ramadhan & Utama, 2019). Figure 6 explains how data flow from the sensor goes through the Fuzzy Logic controller and output data to the actuator.

In the research, Fuzzy Logic is run from a Python program using the SciKit-Fuzzy library. The library uses Mamdani Defuzzification to calculate Fuzzy Logic output. In applying Fuzzy Logic, three stages must be defined: fuzzification, rule base, and defuzzification. From Table 3, the average recommended water parameter is converted into five inputs of Fuzzy membership equally from the minimum and maximum value in each parameter. At this stage, data read from the sensor are converted to Fuzzy Membership. Figure 7 to 9 are the membership functions for each parameter: temperature, DO, and pH.

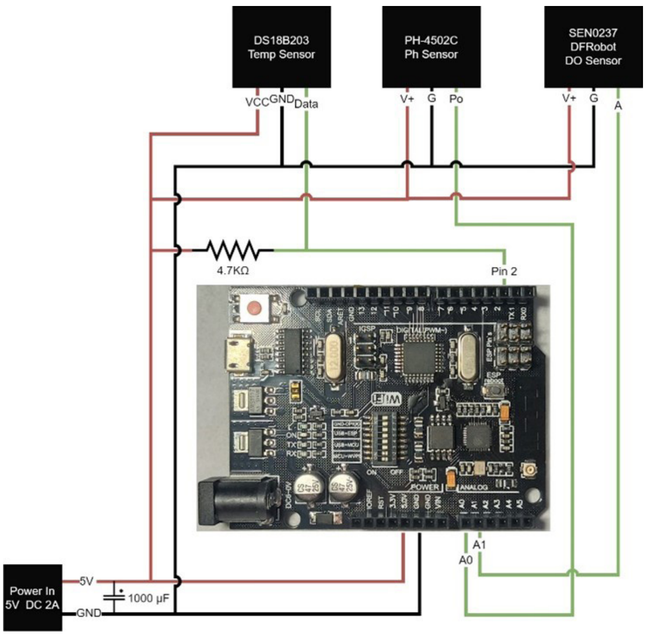

Figure 4 Arduino Uno Built-In ESP8266 and Sensors Schematic

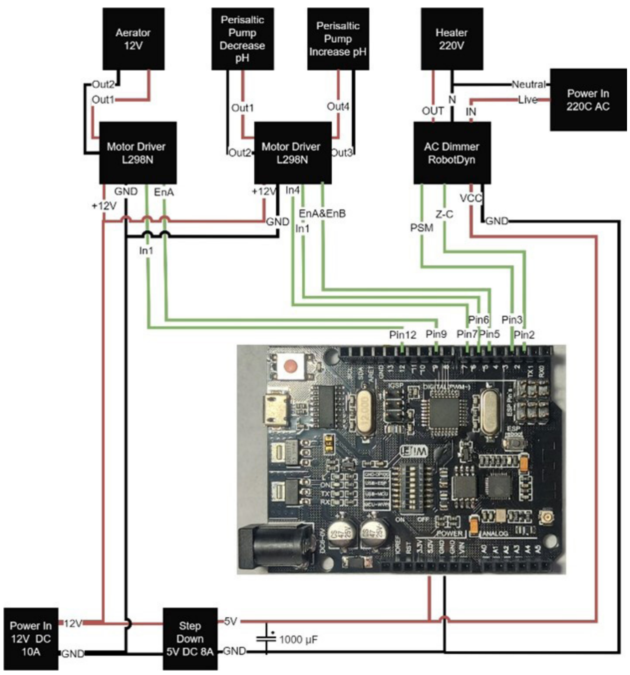

Figure 5 Arduino Uno Built-In ESP8266 and Actuators Schematic

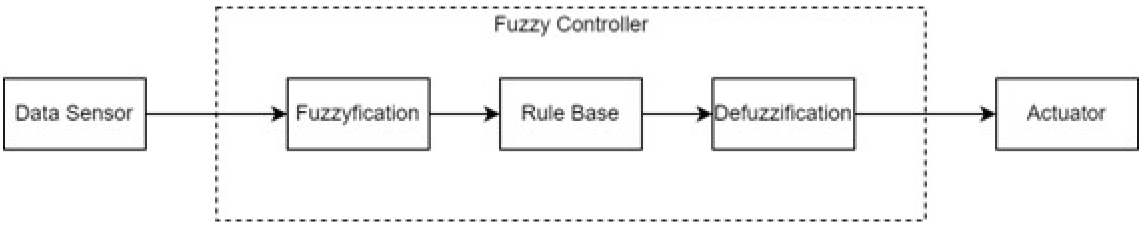

Figure 6 Fuzzy Logic Flow
(Source: Costea et al., 2010; Ramadhan & Utama, 2019)

The rule base is made using the Mamdani Fuzzy inference system. A set of rules must be made to determine when the actuator aerator, heater, and peristaltic pump will turn on and how much intensity the actuator will turn on to improve water quality, according to Table 3. Three groups of rules are implemented in Fuzzy Logic. The first rule turns on the aerator actuator based on input from the DO and temperature sensors. The first rule can be summarized in Table 4. Then, the second rule turns on the actuator heater based on the temperature sensor and the Fuzzy Logic actuator output on the first rule. The second rule can be summarized in Table 5. Next, the third rule turns on the peristaltic pump actuator, which will increase the pH or decrease the pH. This actuator reads the results of the pH sensor and is directly proportional to the results of the actuator. This third rule can be summarized in Table 6 (see Appendices).

At the defuzzification stage, the Mamdani method is used. This method is obtained by taking the center point of the Fuzzy area (Djunaidi et al., 2005). This method can be seen in Equation (4). In this equation, it has X as the input variable, X_i as the i^{th} value of X, and $\mu(X_i)$ as the membership function of X_i. The numerator of the equation is the $Sum(\Sigma)$ of X times the membership function of X, while the denominator is the sum of the membership function of X.

$$\mu(x) = \frac{\sum_{i=1}^{n} x_i\, \mu\,(x_i)}{\sum_{i=1}^{n} \mu\,(x_i)} \tag{4}$$

Defuzzification also changes the output value to output membership. The research uses three actuators for actuator output: heater, aerator, and peristaltic pump. The maximum size for these three actuators is minimum 0 and maximum 100 for the heater, minimum 0 and maximum 100 for the aerator, and minimum -3000 and maximum 3000 for the peristaltic pump.

From these three actuators, a Fuzzy set is made. Each has five membership sets: poor, mediocre, average, decent, and good. This membership is applied to each actuator of the heater in Figure 10, the aerator in Figure 11, and the peristaltic pump in Figure 12. The heater operates within a range of 0 to 100, corresponding to the Pulse Width Modulation (PWM) of an Alternating Current (AC) Dimmer. In contrast, the aerator provides output values ranging from 0 to 100, where 0 signifies that the motor is completely stationary, and a value of 100 signifies that the motor is running at full current draw. The motor of the aerator is controlled by a Motor Driver L298N. The peristaltic pump, on the other hand, delivers output values within the range of -3000 to 3000. In the context of the system,

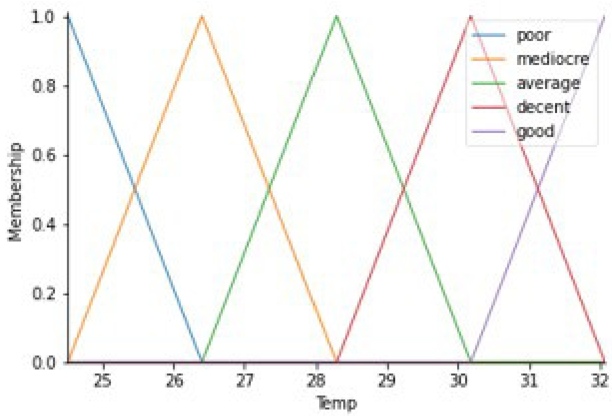

Figure 7 Fuzzy Membership Function of Temperature Input

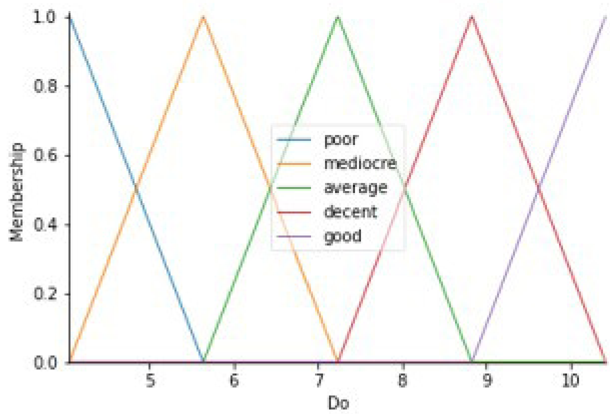

Figure 8 Fuzzy Membership of Dissolved Oxygen (DO) Input

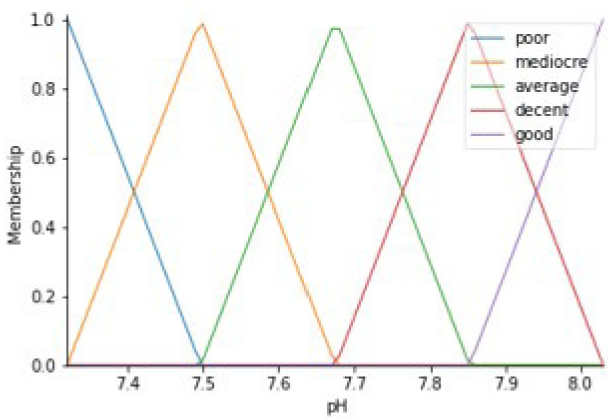

Figure 9 Fuzzy Membership Function of Potential of Hydrogen (pH) Input

Table 4 Aerator Rule Actuator

		Dissolved Oxygen (DO)				
		Poor	**Mediocre**	**Average**	**Decent**	**Good**
Temperature	**Poor**	Aerator(Good)	Aerator(Decent)	Aerator(Average)	Aerator(Mediocre)	Aerator(Poor)
	Mediocre	Aerator(Good)	Aerator(Decent)	Aerator(Average)	Aerator(Mediocre)	Aerator(Mediocre)
	Average	Aerator(Good)	Aerator(Decent)	Aerator(Decent)	Aerator(Average)	Aerator(Mediocre)
	Decent	Aerator(Good)	Aerator(Good)	Aerator(Decent)	Aerator(Average)	Aerator(Average)
	Good	Aerator(Good)	Aerator(Good)	Aerator(Good)	Aerator(Decent)	Aerator(Average)

Table 5 Heater Rule Actuator

		Temperature				
		Poor	**Mediocre**	**Average**	**Decent**	**Good**
Aerator	**Poor**	Heater(Good)	Heater(Decent)	Heater(Average)	Heater(Mediocre)	Heater(Poor)
	Mediocre	Heater(Good)	Heater(Decent)	Heater(Average)	Heater(Mediocre)	Heater(Mediocre)
	Average	Heater(Good)	Heater(Decent)	Heater(Decent)	Heater(Average)	Heater(Mediocre)
	Decent	Heater(Good)	Heater(Good)	Heater(Decent)	Heater(Average)	Heater(Average)
	Good	Heater(Good)	Heater(Good)	Heater(Good)	Heater(Decent)	Heater(Average)

Table 6 Peristaltic Pump Rule Actuator

Potential of Hydrogen (pH)				
Poor	**Mediocre**	**Average**	**Decent**	**Good**
Peristaltic Pump(Good)	Peristaltic Pump(Decent)	Peristaltic Pump(Average)	Peristaltic Pump(Mediocre)	Peristaltic Pump(Poor)

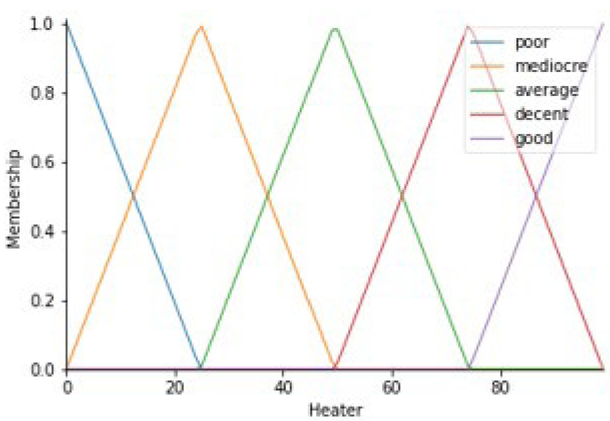

Figure 10 Fuzzy Membership Function of Heater Output

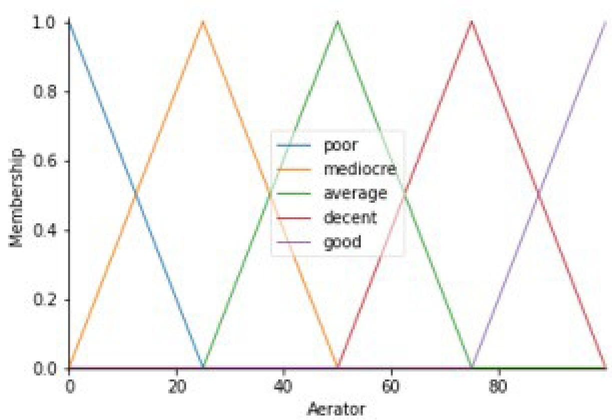

Figure 11 Fuzzy Membership Function of Aerator Output

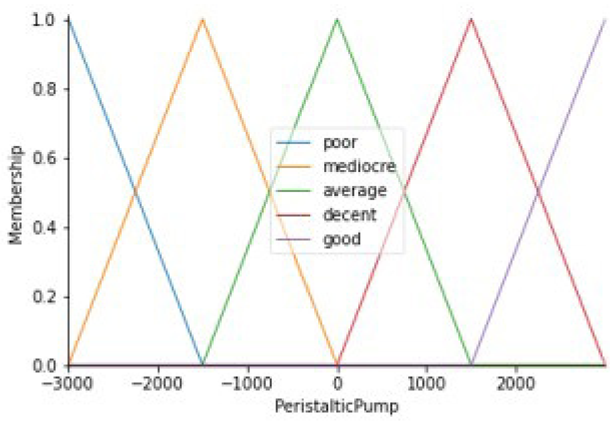

Figure 12 Fuzzy Membership Function of Peristaltic Pump Output

negative Fuzzy Logic results instruct the peristaltic pump to pump seawater, resulting in a reduction of the water's pH. Conversely, positive Fuzzy Logic results prompt the peristaltic pump to dispense CaCO3 water solution, increasing the pH value in the system.

III. RESULTS AND DISCUSSIONS

The sensor successfully reads temperature, DO, and pH at 2,5 minutes intervals, and the actuator can improve and maintain water quality for shrimp using the proposed system. For 30 days, the researchers retrieve sensor data from Arduino ESP 8266 and calculate the data using Fuzzy Logic. Then, output data are sent to the cloud database and displayed through the Application Express (APEX) application from Oracle AS. APEX application is a web application that can connect with the Oracle database, as described in Figure 2. The web created with the APEX application already has a web-responsive feature so that it can be consumed by desktops (Figure 13 (see Appendices)) and mobile devices (Figure 14 (see Appendices)). The reporting page shows line charts between water parameters and their corresponding actuators. The report page can also filter from which date to which date. It also shows the latest received value from Raspberry Pi.

Figure 15 (see Appendices) to 17 (see Appendices) are graphs of sensors recorded for 30 days from 01 Apr 2022 to 30 Apr 2022. Table 4. Each figure represents each model for Fuzzy Logic with corresponding output using the rule base in Tables 4 to 6. Figure 15 (see Appendices) shows temperature and DO sensors to calculate aerator output using the rule base in Table 4. The blue line shows the Fuzzy Logic output of the aerator. Then, the dashed red line represents temperature, and the solid red line represents DO. The output value of the aerator is used to calculate the heater in Figure 16 (see Appendices). In Figure 16 (see Appendices), the value is presented by a solid red line for the aerator, a dashed red line for the temperature sensor, and a solid blue line for the heater output. Both aerator and heater output values follow the rule set previously. Figure 17 (see Appendices), shows the calculated peristaltic pump value based on pH value. Red dots present the output of the peristaltic pump, and a solid black line is used to mark 0 milliseconds. Each dot above the black solid line means that the peristaltic pump doses it to increase the pH level in the water. Vice versa, each dot below the black solid line means that the peristaltic pump doses water to decrease the pH level. The value for each blue dot is calculated by Fuzzy Logic using the rule in Table 6, and the value for pH sensors is represented by the solid red line.

Table 7 (see Appendices), shows the sensor recording results using IoT. It shows temperature values with an average of 32,02 °C, a maximum of 33 °C, a minimum of 27 °C, and a standard deviation of 0,69. Then, the DO sensor results in an average of 7,01 mg/L, a maximum of 8,46 mg/L, a minimum of 5,3 mg/L, and a standard deviation of 0,61. Meanwhile, the pH sensor results have an average of 7,65, a maximum of 8,83, a minimum of 6,17, and a standard deviation of 0,86. To validate the correct value of the water from sensor readings, the researchers use AR8210 DO. Next, temperature sensor tools and the EZ-9901 pH sensor tool compare the IoT sensor reading with actual water conditions. The validation is carried out each week to calculate the error rate, accuracy, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) of the proposed system performance. RMSE is calculated as the square root of the average squared difference between IoT sensors and sensor tools. As for MAE, it is calculated by adding up all the absolute differences and dividing them by the number of test differences. The results for temperature parameters have an average error of 0,94%, accuracy of 99,06%, RMSE of 0,36, and MAE of 0,30. Meanwhile, DO parameters consist of an average error of 3,83%, accuracy of 96,17%, RMSE of 0,34, and MAE of 0,27. Last, pH parameters have an average error of 3,25%, accuracy of 96,75%, RMSE of 0,32, and MAE of 0,25

Shrimps have been cultured for 30 days (01 Apr 2022 to 30 Apr 2022). Figure 18 (see Appendices) shows two aquariums: the left is a research aquarium, and the right is a control aquarium. The research aquarium has an IoT system implemented and monitored. Both aquariums have an aerator, heater, filter pump, and auto feeder, but the control aquarium cannot change the heater and aerator value. Meanwhile, the research aquarium is monitored by a designed IoT system. During the first ten days, shrimps have been taken as samples on the first day (stocking) and last day. From the control aquarium sample, the shrimps are weighed, and body length is measured. The average weight of shrimp at the beginning of stocking is 0,18 g with an average body length of 25,4 mm. At 30 days (Days of Culture (DOC)), it has an average weight of 0,39 g with an average body length of 32,0 mm for the control aquarium and an average weight of 0,50 g with an average body length of 34,6 mm for experiment aquarium. Figure 19 (see Appendices) shows the weight distribution for initial shrimps in control and experiment aquariums on the first day to the thirtieth day. Then, Figure 20 (see Appendices) shows the shrimp's distribution length for the initial day and the length in the control and experiment aquarium on the thirtieth day.

Next, an independent sample T-test is used to check the effectiveness of IoT in the experiment aquarium compared to the control aquarium. Data to calculate the T-test are presented in Table 8 (see Appendices). Then, Table 9 (see Appendices) shows the calculated statistics for both results. Then, two sets of hypotheses are used to determine the experiment result's significant value (p). The experiment result is not statistically significant if a significant value is more than 0,05 ($p \geq 0,05$). Using the null hypothesis (H_0), it can assume the observed difference in experiment and control results due to chance alone. Alternatively, if the significant value is less than 0,05 ($p < 0,05$), the experiment result is statistically significant. So, the researchers can reject the null hypothesis (H_a). It means that the experiment result using IoT increases the growth in shrimp's weight and length.

Weight in the experiment aquarium has a significant increase (weight experiment of Mean (M) = 0,50 g, Standard Deviation (SD) = 0,09 g) compared to the control aquarium (weight control of M = 0,39 g, SD = 0,06 g), with T-test for weight sample of $t(9) = 2{,}939$, $p = 0{,}008$. Since the p-value of 0,008 is less than the commonly chosen significance level of 0.05, it indicates that the weight growth is statistically significant. For length in the experiment aquarium, there is no significant increase (length experiment with M = 34,6 mm and SD = 6,39 mm) compared to the control aquarium (length control experiment with M = 32,0 mm and SD = 5,65 mm) with T-test for length sample $t(9) = 0{,}962$, $p = 0{,}348$. For the length p-value is 0,348, it is greater than the commonly chosen significance level of 0,05. This indicates that the length growth is not statistically significant. In summary, the significant value for weight is less than 0,05 ($p < 0{,}05$), but the length is more than 0,05 ($p \geq 0{,}05$). It can be concluded that using IoT in aquariums only affects weight growth but not length growth for the tested shrimps.

Many factors affect the growth of shrimp length, but the research fails to prove that IoT affects shrimp length. For example, nitrate waste has a negative impact on the growth of shrimp (Valencia-Castañeda et al., 2018). In addition, other parameters, such as stocking density, pond size, and salinity, also affect the growth of the shrimp (Thakur et al., 2018). Hence, further research is needed to prove whether these parameters can help increase the growth of shrimp length.

At the beginning of the stocking, the population was 135 shrimps for the control aquarium and 132 shrimps for the experiment aquarium. At the end of the research on the 30 DOC populations, it is 113 shrimps for the control aquarium and 119 shrimps for the experiment aquarium. From the experiment aquarium, the average shrimp weight at the stocking beginning is 0,39 g with a length of 25,40 mm. At 30 days, the control aquarium's shrimps have an average weight of 0,39 g with a length of 32,00 mm. Then, the experiment aquarium's shrimps have an average weight of 0,50 g with a length of 34,60 mm.

Data population from beginning to end of research can be calculated using the %SR formula in Equation (1) by dividing the end population by the beginning population and multiplying it by 100%. Then, weight data can be calculated with the SGR formula in Equation (2) by subtracting the end weight from the beginning weight and dividing it by the number of days, and multiplying it by 100 (in this case, 30 days). This formula results in the growing shrimp weight rate for each DOC. Overall shrimps' growth length can be calculated by subtracting the end length from the beginning length using Equation (3). Table 10 (see Appendices) shows a comparison of the control aquarium versus the experiment aquarium. By using the proposed system in Figure 2, experiment aquarium shows increasing growth potential in shrimps' population, weight, and length than control aquarium. However, the increase in length is not significant enough.

IV. CONCLUSIONS

Using the proposed system with IoT and Fuzzy Logic improves shrimp's survival rate, weight, and growth compared to traditional system. The finding implies that using technology, such as IoT and Fuzzy Logic, improves the quality and quantity of cultured shrimp. In the hardware and software architecture design, the proposed system can be scaled horizontally or vertically to meet shrimp farmers' needs with multiple ponds on their farms. The proposed system is also successful in improving and maintaining water parameters. It shows a potential growth in population and weight of the shrimps compared to non-IoT counterparts.

Shrimp's growth length needs further research as the research only studies temperature, pH, and DO. Other water parameters, such as nitrate, salinity, dissolved inorganic nutrients, alkalinity, hardness, calcium, magnesium, potassium, chlorophyll-a, turbidity, and parameters outside water, also need to be studied. In addition, other aspects like density and pond size also affect the survivability, weight, and length of cultured shrimps. Future research can also develop an IoT system that reads parameters not included in the research. The results may improve and maintain water quality. Different types of Fuzzy Logic, like Sugeno, can also be compared with these parameters. Then, future research can investigate whether these parameters and different Fuzzy Logic systems can increase the survivability, weight, and length of shrimps.

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APPENDICES

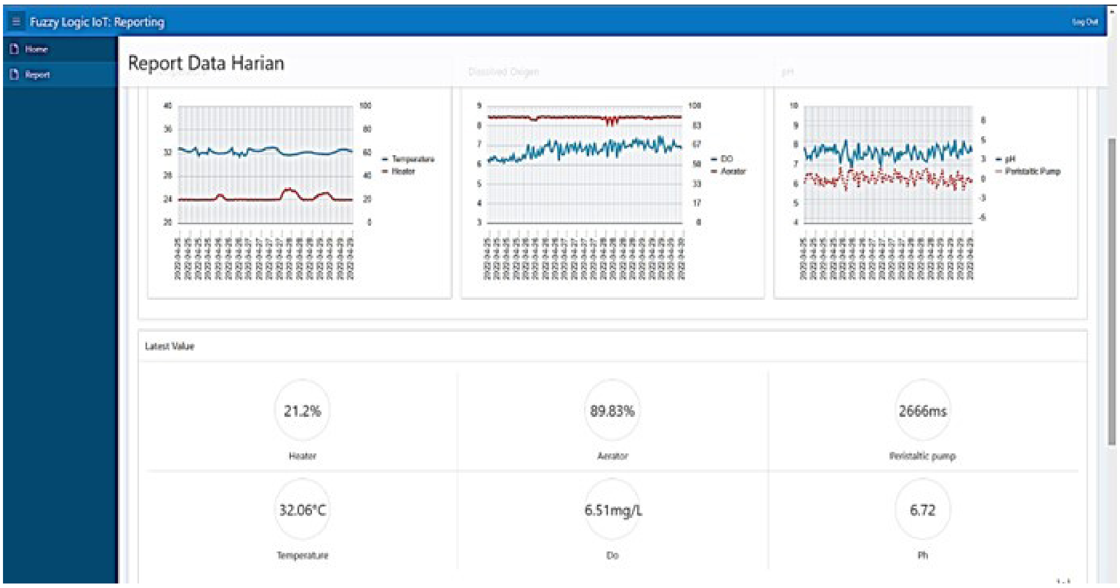

Figure 13 Report Showing Periodic Value and Latest Value as Viewed from Desktop

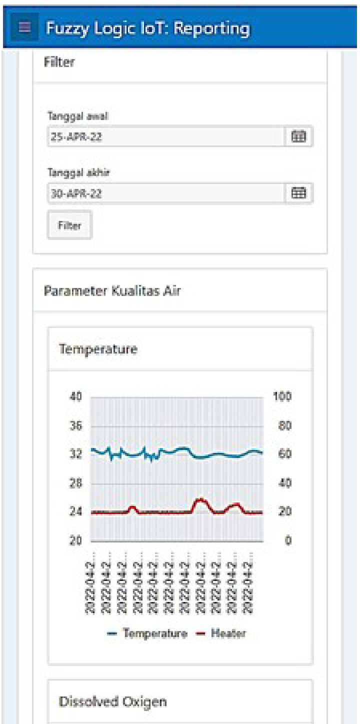

Figure 14 Report Showing Periodic Value and Latest Value as Viewed from Mobile Device

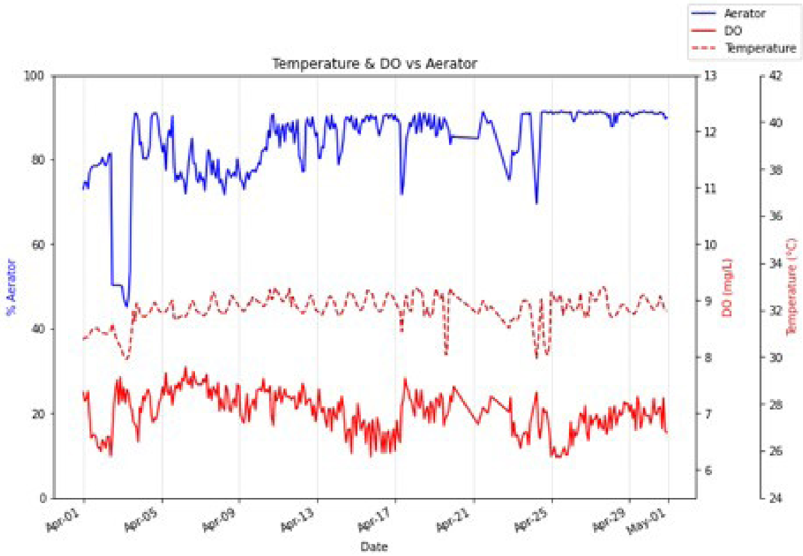

Figure 15 Recorded Temperature and Dissolved Oxygen (DO) vs. Aerator

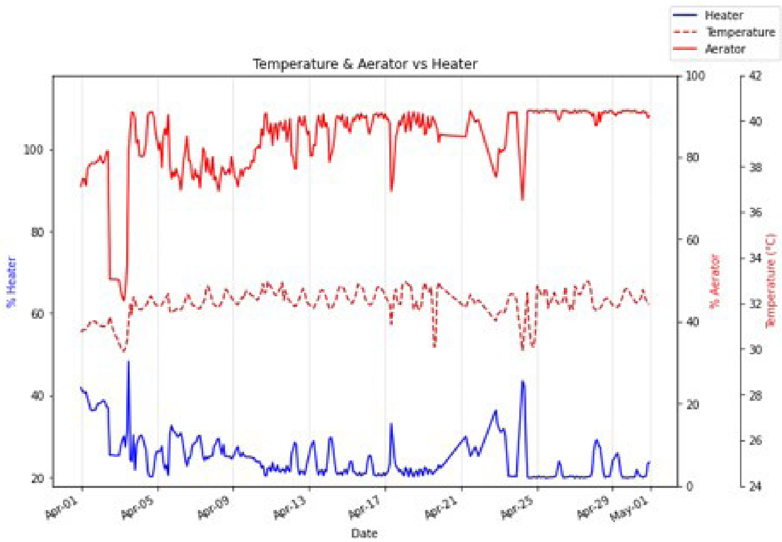

Figure 16 Recorded Temperature and Aerator vs. Heater

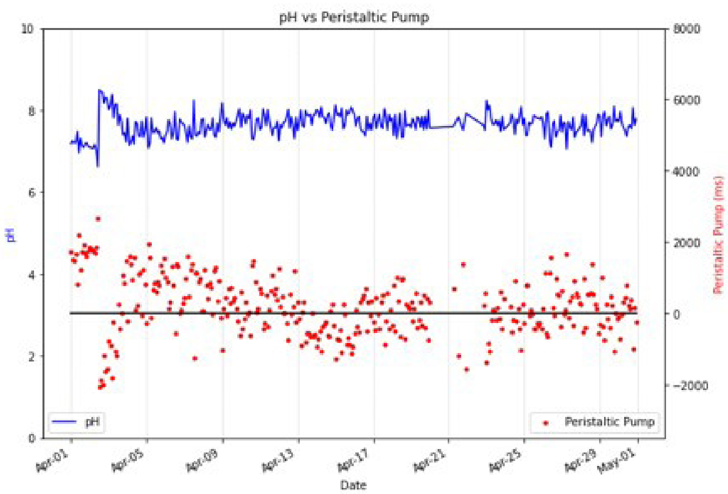

Figure 17 Recorded pH vs. Peristaltic Pump

Table 7 Calibration of Internet of Things (IoT) Sensor vs. Independent Measurement

Water Parameter	Date Time	IoT Sensor Read	Sensor Tools Read	Difference	Unit of Measurement (UoM)	Error (%)	Accuracy (%)
Temperature	03 Apr 2022 18:45	32,02	32,30	-0,28	°C	0,86	99,14
Temperature	13 Apr 2022 18:48	32,57	32,40	0,17	°C	0,52	99,48
Temperature	17 Apr 2022 09:50	31,22	31,10	0,12	°C	0,37	99,63
Temperature	25 Apr 2022 13:31	32,30	32,00	0,30	°C	0,92	99,08
Temperature	29 Apr 2022 17:58	32,66	32,00	0,66	°C	2,05	97,95
					Average (AVG)	0,94	99,06
					Root Mean Square Error (RMSE)	0,36	
					Mean Absolute Error (MAE)	0,30	
Dissolved Oxygen (DO)	03 Apr 2022 18:45	6,75	7,30	-0,55	mg/L	7,48	92,52
Dissolved Oxygen (DO)	13 Apr 2022 18:48	6,66	6,80	-0,14	mg/L	2,00	98,00
Dissolved Oxygen (DO)	17 Apr 2022 09:50	7,52	7,00	0,52	mg/L	7,36	92,64
Dissolved Oxygen (DO)	25 Apr 2022 13:31	6,22	6,30	-0,08	mg/L	1,33	98,67
Dissolved Oxygen (DO)	29 Apr 2022 17:58	6,74	6,80	-0,06	mg/L	0,96	99,04
					Average (AVG)	3,83	96,17
					Root Mean Square Error (RMSE)	0,34	
					Mean Absolute Error (MAE)	0,27	
Potential of Hydrogen (pH)	03 Apr 2022 18:45	7,60	7,67	-0,08	-	0,98	99,02
Potential of Hydrogen (pH)	13 Apr 2022 18:48	7,36	7,36	0,00	-	0,04	99,96
Potential of Hydrogen (pH)	17 Apr 2022 09:50	8,19	7,71	0,48	-	6,24	93,76
Potential of Hydrogen (pH)	25 Apr 2022 13:31	8,04	7,57	0,47	-	6,26	93,74
Potential of Hydrogen (pH)	29 Apr 2022 17:58	7,50	7,71	-0,21	-	2,74	97,26
					Average (AVG)	3,25	96,75
					Root Mean Square Error (RMSE)	0,32	
					Mean Absolute Error (MAE)	0,25	

Figure 18 Research Aquarium (Left) and Control Aquarium (Right)

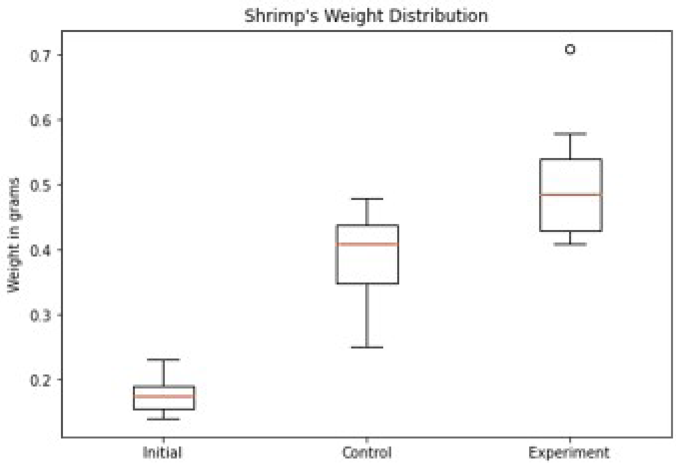

Figure 19 Shrimp's Weight Distribution in Gram

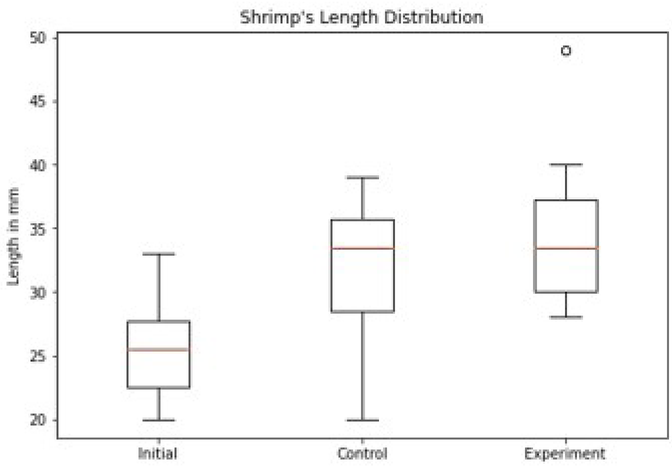

Figure 20 Shrimp Length Distribution in Millimeter

Table 8 Measurement Result Using Ten Samples for Control and Experiment Aquariums

	Length (mm)		Weight (g)	
#	**Control**	**Experiment**	**Control**	**Experiment**
1	20	38	0,25	0,55
2	32	34	0,39	0,49
3	35	28	0,43	0,41
4	35	49	0,43	0,71
5	36	33	0,44	0,48
6	37	35	0,46	0,51
7	39	29	0,48	0,42
8	30	40	0,37	0,58
9	28	30	0,34	0,43
10	28	30	0,34	0,43
$\bar{x}$	**32,0**	**34,6**	**0,393**	**0,501**

Table 9 Statistic Results of Control and Experiment Aquariums

	Weight (g)		Length (mm)	
N=10	**Control**	**Experiment**	**Control**	**Experiment**
Mean	0,392	0,501	32,000	34,600
Min	0,250	0,410	20,000	28,000
Max	0,480	0,710	39,000	49,000
Std. Dev	0,069	0,093	5,656	6,397
Std. Error Mean	0,022	0,029	1,788	2,023

Table 10 Assessment Results Using %SR, SGR, and Pm Equations

	Control	Experiment
In	135	132
Fn	113	119
%SR	**84%**	**90%**
Days	30	30
IBW (g)	0,18	0,18
FBW (g)	0,39	0,50
SGR	**0,70**	**1,07**
P0 (mm)	25,4	25,4
Pt (mm)	32,0	34,6
Pm	**6,6**	**9,2**

Note: %SR: survivability percentage, Fn: final number of juvenile shrimps, In: initial number of juvenile shrimps, SGR: Specific Growth Rate, FBW: final body weight, IBW: initial body weight, Pm: mean length of shrimp, Pt: average length of shrimp at the end of the research, and P0: average length of shrimp at the beginning of the research.