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Original Research Paper

Arduino-Based Heart Rate Monitoring System Using Mamdani Fuzzy Logic

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Abstract: Heart disease remains one of the leading causes of death worldwide, highlighting the need for an early and accurate monitoring system. This research aims to design an Arduino-based heart rate monitoring system that integrates the MAX30102 pulse sensor and the MLX90614 body temperature sensor. Using the Mamdani fuzzy logic method, the system classifies a user's health condition into three categories: healthy, alert, and at risk, based on inputs from heart rate, body temperature, and age. A total of 27 fuzzy rules are applied, and the results are displayed in real-time via a laptop monitor. Compared to conventional heart monitoring methods, this system offers a lower-cost and portable solution suitable for household use. Preliminary tests conducted on six samples yielded an average error rate of 16.3% (beats per minute, bpm) for the pulse sensor, which falls into the medium error category, and 3.95% (°C) for the temperature sensor, which falls into the low error category. The system was evaluated by comparing sensor readings with those of standard commercial devices, indicating acceptable accuracy for a prototype stage. While the system functions well, its performance could be further improved with enhanced sensor accuracy, wireless data transmission, and integration with mobile applications. Future developments could also focus on increasing the sample size and benchmarking against clinical-grade devices to strengthen reliability and usability. The proposed system is unique in combining heart rate, body temperature, and age data through fuzzy logic to provide real-time classification of health status in a low-cost and portable design, making it a promising tool for household-based preventive heart health monitoring.

Keywords: Arduino, Biomedical Sensors, Health Technology, Heart Rate Monitoring, Mamdani Fuzzy Logic.

1. Introduction

Cardiovascular diseases remain a predominant contributor to global morbidity and mortality, posing a significant and sustained challenge to public health systems worldwide. According to epidemiological data released by the World Health Organization (WHO), approximately 17.8 million deaths occur annually as a result of cardiac and vascular conditions, including myocardial infarction, arrhythmic syndromes, and congestive heart failure [1] [2]. Among the critical physiological indicators linked to these pathologies, heart rate has been identified as a primary metric for evaluating cardiac function and detecting potential abnormalities at an early stage. One important indicator in monitoring heart health is heart rate (BPM - Beats Per Minute) [3]. An abnormal heart rate is often the first symptom or sign of a heart problem, so regular monitoring is very important in preventing serious complications [4].

Several studies have shown that heart rate has a significant relationship with heart disease. According to, a heart rate that is too low (<60 BPM - Bradycardia) can lead to insufficient blood flow to vital organs, potentially resulting in dizziness, fatigue, and heart failure [1]. Meanwhile, too high (>100 BPM - Tachycardia) increases the risk of cardiovascular complications such as heart failure, sudden cardiac arrest, and stroke [5]. In patients with heart failure, a heart rate ≥70 BPM has a strong correlation with increased rehospitalization and mortality rates. This suggests that abnormal heart rate can be a key indicator in monitoring overall heart health [4].

Besides heart rate, other factors that affect heart health are age and body temperature. Age is an important factor because as we get older, the risk of cardiovascular disorders increases [6]. Body temperature also plays a role in determining heart health, as both hyperthermia (high body temperature) and hypothermia (low body temperature) can affect the heart and blood circulation [7]. An increase in body temperature, for example, can speed up the heart rate and increase the heart's workload [8]. Therefore, these three things (heart rate, age, and body temperature) are important to provide a comprehensive picture of the heart's condition. Real-time heart rate monitoring remains a key step in detecting and preventing potentially fatal heart disorders [9].

In order to support health monitoring, a system is needed that can accurately detect changes in heart rate and provide early warning of abnormalities [5]. This research develops an Arduino-based heart rate monitoring system using a pulse sensor integrated with Mamdani fuzzy logic [10] [11]. The use of Mamdani fuzzy logic in this system aims to provide a more flexible and accurate decision in capturing uncertainty in data from heart rate measurements [12] [13]. Different from conventional methods that are firm, fuzzy methods allow the system to provide more realistic assessments according to individual conditions [14]. With the development of this system, it is expected that people can monitor their heart conditions independently at an affordable cost and with high accuracy [15]. This system also provides a solution for the early detection of heart disorders, which can help minimize the risk of serious complications in the future [16].

Research conducted by [4] [16] aims to produce a system design that is able to detect heart rate and human breathing rate effectively . This research uses two types of input, namely the MAX30100 sensor to detect heart rate and oxygen in the blood, and Bluetooth as a medium for sending data to other devices [4]. The method used is Sugeno fuzzy logic, which produces outputs in the form of linear or constant functions [11].

However, this research has several limitations that become gaps for further development. The study only used heart rate and respiratory rate as the main variables without considering age and body temperature asb≤x≤c important factors in heart health analysis [7]. Age affects the interpretation of measurement results because the normal heart rate limit in young individuals is different from that of adults or elderly individuals [9]. Body temperature also has a close relationship with heart rate, where hyperthermia (high body temperature) or hypothermia (low body temperature) conditions can cause significant changes in heart rate and increase the workload of the heart [7]. Another limitation lies in the Sugeno fuzzy method used in the previous study [11] [14]. This method only produces output in the form of fixed numerical values, so it is less able to capture the uncertainty and biological variability contained in heart rate, age, and body temperature data [12] [13] [16].

This research aims to overcome the previous limitations by developing an Arduino-based health monitoring system that integrates the MAX30102 sensor as the main sensor to detect heart rate and the accurate monitoring MLX90614 sensor to measure body temperature [3] [17]. In addition to these two sensors, the age variable is also included as an important parameter in the assessment of heart health conditions [9]. The system is designed to analyze three main variables: heart rate, age, and body temperature, to provide a more comprehensive and accurate assessment of a person's physiological condition [7]. To support flexibility in decision-making, the system applies Mamdani fuzzy logic that is able to capture uncertainty and biological variations, and produces output in the form of qualitative categories of Healthy, alert, and at risk [11] [18]. In this study, heart rate data is grouped into three distinct categories based on BPM: bradycardia, characterized by a heart rate below 60 BPM; normal, ranging from 60 to 100 BPM; and elevated, exceeding 100 BPM [16]. Age is segmented into three groups: young individuals, aged 25 years or younger; adults, between 25 and 45 years; and elderly individuals, older than 45 years [12]. Meanwhile, Body temperature is classified into three ranges: low, below 36°C; normal, between 36°C and 37°C; and high, above 37°C. [15]. With the combination of these three variables and the utilization of the Mamdani fuzzy method, the system is expected to be able to provide real-time classification of heart health conditions and detect potentially dangerous conditions early on [3] [17].

With the integration of these three variables and the application of Mamdani fuzzy logic, this research not only offers a more flexible and accurate monitoring system but also provides more comprehensive analysis capabilities than previous research [8]. The test results of this research are expected to demonstrate the accuracy of the system in monitoring heart rate, age, and body temperature in real-time, and prove the superiority of the Mamdani fuzzy method in providing a more detailed and adaptive classification of individual physiological conditions [11].

The gap of this research lies in the integration of three variables (heart rate, age, and body temperature) as factors that affect the classification of heart health using the Mamdani fuzzy logic method, which has not been applied in previous studies [19]. Therefore, this research aims to develop an Arduino-based heart rate monitoring system using a pulse sensor integrated with Mamdani fuzzy logic methodology to provide more adaptive and accurate measurement results according to the categories of heart rate, age, and body temperature [7].

Based on this background, the author designed an Arduino-based heart rate monitoring system for maintaining and controlling heart rate in humans [20]. The use of Arduino as the main controller of the system and the application of Fuzzy Logic Mamdani as control was chosen because of its ability to regulate heart rate effectively [21].

2. Literature Review

2.1. Heart Rate

Heart rate, expressed in BPM, which is usually expressed in units of BPM [4] [7] [19]. Heart rate is one of the vital parameters that indicate a person's general physiological condition [12] [16]. As an important indicator of the cardiovascular system, heart rate provides information on the effectiveness of the heart in pumping blood that carries oxygen and nutrients throughout the body [2] [8] [15]. In the context of health [3] [22], heart rate measurements are often taken periodically to detect early heart abnormalities, such as bradycardia (slow heart rate) or tachycardia (fast heart rate), that can be life-threatening [1] [20] [21]. Current technological developments allow heart rate to be monitored in real-time using various sensors, so that health monitoring can be done independently by individuals [10] [23]-[25].

2.2. Fuzzy Logic

A fuzzy set refers to a group of elements where each element is assigned a degree of membership, expressed through a membership function denoted by μ. This function represents how strongly an element is associated with the set, using values that range continuously between zero and one [11]. In contrast to classical logic, which limits classification to absolute inclusion or exclusion, fuzzy logic allows for partial membership, making it suitable for handling uncertainty and vagueness in real-world systems [1] [12]. A membership degree of zero signifies that an element is entirely outside the set, while a degree of one indicates full inclusion. Intermediate values reflect varying levels of association, allowing more flexible reasoning in complex or imprecise scenarios [9] [26].

Membership function:

$$\mu[x] = \begin{cases} 0; & x \le a, \text{or } x \ge c \\ (x-a)/(b-a); & a \le x < b \\ (b-x)/(c-b); & b \le x \le c \end{cases} \quad (1)$$

Description:
μ[x] is the membership value of$x$ to the fuzzy set.
a is the boundary where the membership function starts to rise (membership value 0 to the left of$a$ aa).
b is the peak point of the membership function (membership value 1 at$b$ b).
c is the final limit of the membership function decreases back to 0.

If $x \leq a$ x≤a, or $\geq c$ x≥c is the membership value is 0, because$x$ x is outside the relevant range.
If $a \leq x < b$, a≤x<b is the membership function rises linearly from 0 to 1.
If $b \leq x \leq c$, b≤x≤c is the membership function linearly decreases from 1 to 0.

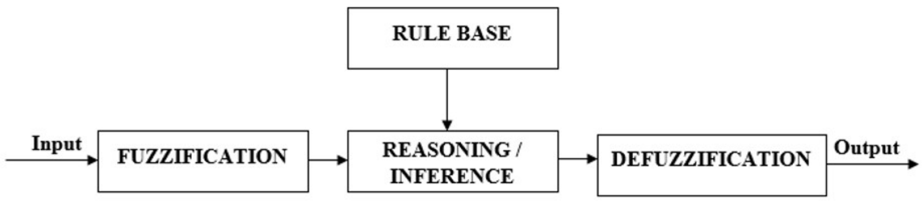

Figure 1. Fuzzy Logic Structure

2.3. Fuzzy Mamdani

In general, fuzzy logic consists of 3 methods, including Mamdani, Tsukamoto, and Sugeno [1] [11] [27]. Mamdani fuzzy logic is one of the existing methods with excellent flexibility and tolerance of existing data [16] [28]. This method can be easily understood and accepted by humans due to the representation of input into an easy machine [1] [12]. Originating from seminal efforts in computational reasoning during the mid-1970s, the Mamdani fuzzy inference architecture, attributed to Ebrahim Mamdani's foundational contribution in 1975 [11] [14], has emerged as a cornerstone in the formalization of approximate logic systems. Its adoption is predicated on the model's intrinsic capacity to reconcile ambiguity within non-crisp datasets, offering a linguistically-driven framework for rule-based decision environments. Rather than imposing rigid binary thresholds, the Mamdani approach facilitates gradational mapping between antecedent conditions and consequent outputs. The mechanism governing this fuzzy inferential construct is articulated through a structured sequence of functional stages, as elaborated in the subsequent inferential scheme:

1. Fuzzy Set Formation (Fuzzyfication)
   The first stage is to convert a crisp input value into a fuzzy input. However, the variables to be used, whether input or output variables, must first be determined [13].

2. Implication Function
   The second stage involves compiling the rules to be used, which usually take the form of implications that map input variables to output variables. [17] In this study, the implication mechanism is based on the minimum (MIN) operator, which selects the smallest membership value between the input condition and the rule strength for each evaluation. Mathematically, this is expressed as:

   $$\mu(x_i) = \min(\mu_a(x_i), \mu_b(x_i)) \quad (2)$$

   In this formulation, $\mu_a(x_i)$ represents the degree of membership of the i-th input to the fuzzy set, while $\mu_\beta(x_i)$ refers to the membership value associated with the i-th rule. The output of the implication is determined by whichever of these two values is smaller, thus reflecting the conservative nature of the MIN operator in combining fuzzy evidence.

3. Rule Composition
   The third stage is the composition of rules that map several rules that are fulfilled about fuzzy values [12]. If several rules are fulfilled, then inference is obtained based on the collection and

correlation between the available rules [11]. The method generally used is the Max method. The Max method is the selection of the largest value from the output value of a rule [29]. The general form of this rule composition is as follows:

$$\mu_{xi} = \max_{(usf\,(xi)),\mu_{kf\,(xi))}} \tag{3}$$

Description:
$\mu_{sf}(x_i)$ is the fuzzy output membership value up to rule i
$\mu_{kf}(x_i)$ is the membership value of the fuzzy rule i-th

4. Defuzzyfication
The final stage is defuzzification, where the fuzzy output obtained from the previous stage is converted into concrete values that can be used in real-world systems [21]. In the Mamdani method, several defuzzification methods can be used, such as Centroid, Bisector, Mean of Maximum, Largest of Maximum, and Smallest of Maximum.

$$Z_0 = \int_a^b z.\mu(z)dz \,/\, \int_a^b \mu\,(z)dz \tag{4}$$

Description:

Z_0	Crisp output values resulting from the defuzzification process
$\dot{z}$	Linguistic variables or domains of fuzzy sets
$\int_a^b z.\mu(z)dz$	It is an integral of the product of the value z and its membership degree

The formula used in each defuzzification method will produce different output values based on its respective methodologies. Therefore, the Mamdani Fuzzy Logic structure includes Fuzzy Set Formation (Fuzzification), Implication Functions, Rule Composition, and finally, defuzzification to produce the final result based on fuzzy logic [30].

2.4. Previous Research

Previous studies on Arduino-based health monitoring systems have shown various innovations in measuring heart rate, oxygen saturation, and body temperature [7]. Research by [4] developed a device for detecting early symptoms of hypoxia using the Max30100 sensor, which showed high accuracy with an average error of 2.96% for oxygen saturation and 2.86% for heart rate. Research by [12] designed a health identification system capable of measuring heart rate, oxygen levels, and body temperature with accuracies of 99.25%, 96.67%, and 97.60%, respectively. Research by [10] successfully created an Arduino Mega-based prototype that demonstrated high accuracy in heart rate measurement, along with an intuitive user interface. This researh by [1] demonstrated the effectiveness of fuzzy-based methods in processing health data for early detection purposes [2] designed a telemetry-based heart rate monitoring device that can function up to a distance of 490 meters with an average error of 0.85%. And [5], developed a health monitoring system utilizing the AD8232 sensor for heart rate detection and the DS18B20 sensor for body temperature measurement. The system yielded satisfactory measurement accuracy, highlighting its potential for reliable physiological data acquisition. Overall, this research reflects notable advancement in the development of accessible and efficient healthcare monitoring technologies.

3. Methodology

The research was conducted at the Haris Success Doctor Practice Clinic located on *Jln. Lembaga No.2, Tanjung Rejo, Kecamatan Percut Sei Tuan, Kabupaten Deli Serdang*, utilizes a quantitative approach to evaluate the accuracy and reliability of an Arduino-based heart rate monitoring system employing a pulse sensor. Data collection involved two primary methods: observation and literature study, with a total of six respondents selected based on specific inclusion criteria, including individuals aged between 18 and 70 years, without a history of cardiovascular diseases or other health conditions that could affect heart rate or body temperature, and who provided consent to participate. The collected data included heart rate (measured in BPM), body temperature (measured in °C), and

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age (in years), using the MAX30102 pulse sensor for heart rate and the MLX90614 sensor for body temperature measurement.

Testing scenarios were designed to assess the system's performance under various conditions, including normal resting states, light physical activity, and stress-inducing situations, to evaluate the system's ability to classify health conditions accurately based on the input variables. To assess the validity and reliability of the system, the readings from the MAX30102 pulse sensor were compared against a standard oximeter, while the MLX90614 sensor's body temperature readings were compared with a calibrated thermometer. The percentage error rates for both heart rate and body temperature measurements were calculated to determine accuracy, using specific formulas for each measurement. Additionally, statistical analysis was performed to calculate average error rates, and multiple trials were conducted under the same conditions to ensure consistent results. By incorporating these components into the methodology, the research aims to enhance the reproducibility and scientific validity of the findings, providing a robust framework for evaluating the effectiveness of the Arduino-based heart rate monitoring system. The stages of the research framework used are as follows:

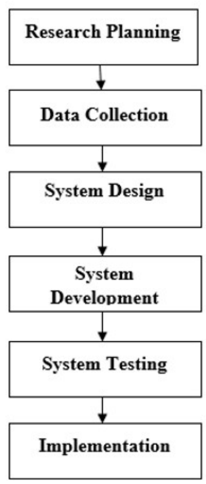

Figure 2. Research Framework

To implement Mamdani fuzzy logic in a decision-making process, a series of structured steps must be followed. These stages are outlined as follows:

1. Fuzzy Set Formation: In this step, input and output variables are represented by fuzzy sets defined using linguistic terms. Each set is equipped with a membership function that assigns a degree of relevance to given values.
2. Implication Function Application: The implementation function used in Mamdani fuzzy logic is the minimum (min) function. It connects a set of fuzzy inputs with a set of fuzzy outputs.
3. Rule Composition: The method used to perform inference in fuzzy systems is the maximum (max) method. In general, the rule can be written as follows: usf [Xi] = max (usf [Xi], ukf [Xi]). With: usf [Xi] = membership value of the fuzzy solution to the i-th rule, ukf [Xi]) = membership value of the i-th rule fuzzy consequence.
4. Defuzzification: In the Mamdani rule composition, defuzzification is done by the weighted average (WA) method. This method takes the center point of the fuzzy region as the sharp solution. This is done to convert the fuzzy value obtained from the previous step into a single value that can be used in practical applications.

Thus, these stages explain the systematic process in Mamdani's fuzzy logic for solving complex problems. An example of the tool design to be assembled is shown in the Figure 3.

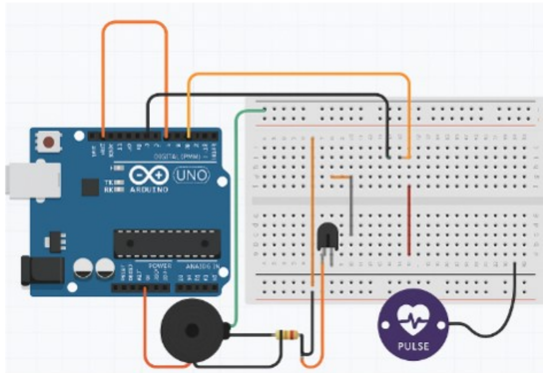

Figure 3. Heart Rate Monitoring System Design

To provide a clearer picture of the workflow of the designed system, a flowchart was created to explain the overall process stages. This flowchart includes the sequence of steps starting from sensor data acquisition, data processing using the Mamdani fuzzy method, and determining the user's health condition category. With this flowchart, it is hoped that readers can understand the processes occurring within the system in a more systematic and structured manner. The system workflow can be seen in Figure 4 System Flowchart.

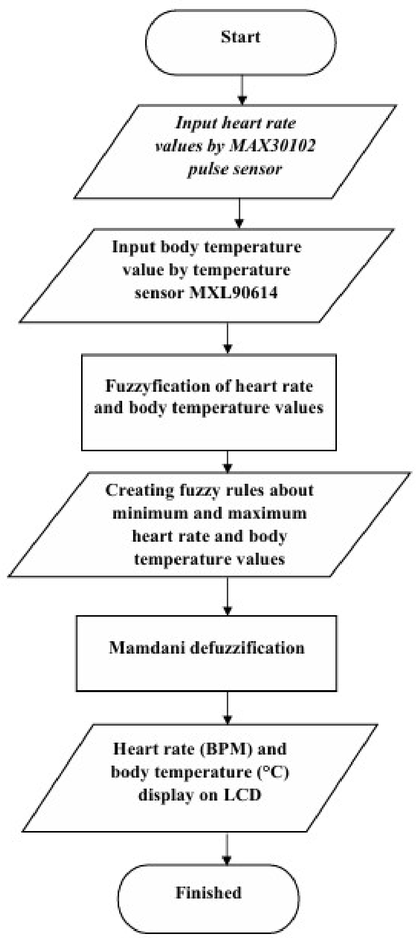

Figure 4. System Flowchart

4. Findings and Discussion

4.1. Finding

Data processing is the process of processing measurement data from an Arduino-based heart rate monitoring system that uses MAX30102 series pulse sensors and MLX90614 sensors. The processed data consists of heart rate, body temperature, and age. The data obtained is then processed using Mamdani fuzzy logic to produce health condition information, which is the basis for decision-making.

Table 1. Input Data of fuzzy variables for Heart Rate Monitoring System

No	Fuzzy Variable	Linguistic Category	Definite Value (Crips)	Unit
1	Heart rate	Bradycardia	50	BPM
		Normal	70	BPM
		Hight	120	BPM
2	Body Temperature	Low	35	ºC
		Normal	36.3	ºC
		Hight	39	ºC
3	Age	Young	23	Years
		Adult	39	Years
		Elderly	60	Years

Based on Table 1, each of these variables will be formed into a fuzzy membership function. The membership function is as follows:

Table 2. Heart Rate Variable Set

Input Variable	Fuzzy set	Reader Universe	Domain
Heart Rate	Bradycardia	0-150bpm	0 - 40 - 60
	Normal		60 - 80 - 100
	Hight		100 - 125 - 150

After performing the fuzzification process on the variables, the next step is to draw a graph of the variable membership function.

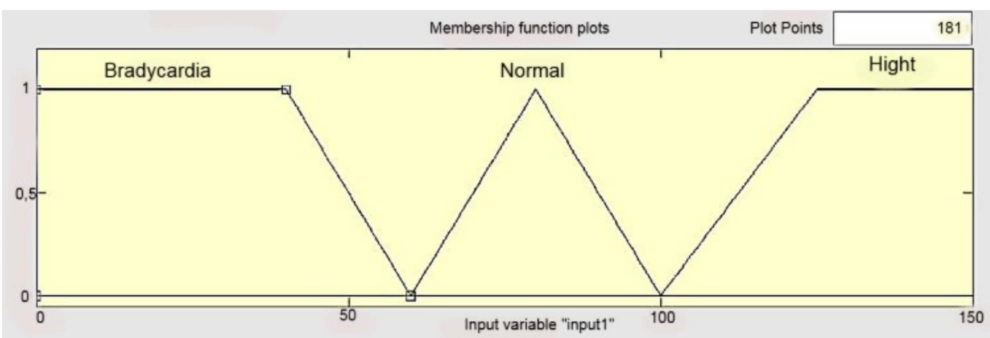

Figure 5. Heart Rate Membership Function

Based on Table 2, heart rate values are divided into three fuzzy categories, namely bradycardia, normal, and high. The membership function for each category is organized based on the shape of an ascending, triangular, and descending graph. The determination of this membership function refers to the heart rate range in BPM as follows:

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$$\mu\text{Bradycardia } [50] \left\{ \frac{60-50}{60} = 0{,}16 \right. \tag{5}$$

$$\mu\text{Normal } [70] \left\{ \frac{70-60}{20} = 0{,}5 \right. \tag{6}$$

$$\mu\text{Hight } [120] \left\{ \frac{120-100}{50} = 0{,}4 \right. \tag{7}$$

Table 3. Body Temperature Variable Set

Input Variable	Fuzzy Set	Reader Universe	Domain
Body Temperature	Low Normal Hight	34°C - 40°C	34 - 35 - 36 36 – 36.5 - 37 37 – 38.5 - 40

After performing the fuzzification process on the variables, the next step is to draw a graph of the variable membership function.

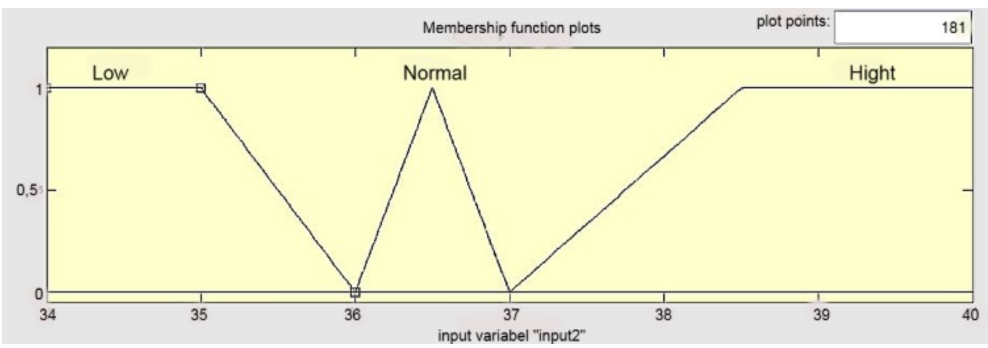

Figure 6. Body Temperature Membership Function

Based on Table 3, body temperature values are grouped into three fuzzy categories, namely low, normal, and high. The membership function for each category is arranged based on the shape of an ascending, triangular, and descending graph. The determination of this membership function refers to the range of body temperature in degrees centigrade (°C) as follows:

$$\mu\text{Low } [35] \left\{ \frac{36-35}{2} = 0{,}5 \right. \tag{8}$$

$$\mu\text{Normal } [36{,}3] \left\{ \frac{36{,}3-36}{0{,}5} = 0{,}6 \right. \tag{9}$$

$$\mu\text{Hight } [39] \left\{ \frac{39-37}{37} = 0{,}6 \right. \tag{10}$$

Table 4. Set of Age Variables

Input Variable	Fuzzy Set	Reader Universe	Domain
Age	Young Adults Elderly	0-70 years old	0 - 17 - 25 25- 35- 45 45 - 60 - 70

After performing the fuzzification process on the variables, the next step is to draw a graph of the variable membership function.

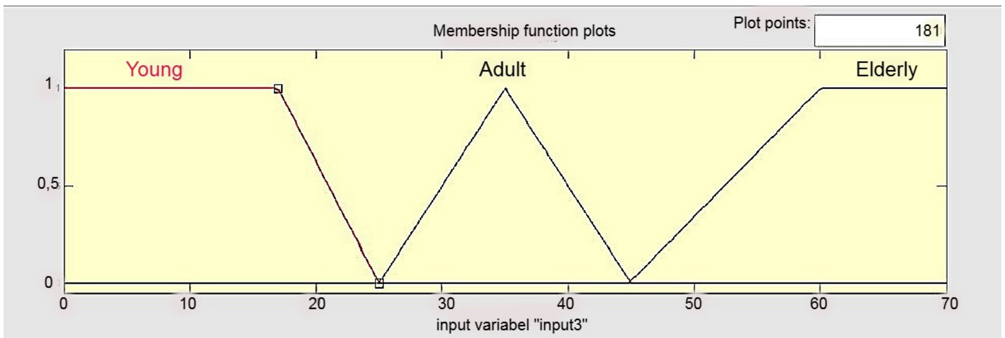

Figure 7. Age Membership Function

Based on Table 4, age values are grouped into three fuzzy categories, namely young, adult, and elderly. The membership function for each category is arranged based on the shape of an ascending, triangular, and descending graph. The determination of this membership function refers to the age range in years as follows.

$$\mu Young\,[23]\ \begin{cases} \frac{25-23}{5} = 0{,}4 \end{cases} \tag{11}$$

$$\mu Adult\,[39]\ \begin{cases} \frac{45-39}{10} = 0{,}6 \end{cases} \tag{12}$$

$$\mu Elderly[60]\ \ - \ 1 \tag{13}$$

Table 5. Heart Health Status Set

Input Variable	Fuzzy Set	Reader Universe	Domain
Heart Health Status	At Risk Alert Healthy	30-90	30 - 30 - 50 45 - 57 - 70 65 - 90 - 90

After performing the fuzzification process on the variables, the next step is to draw a graph of the variable membership function.

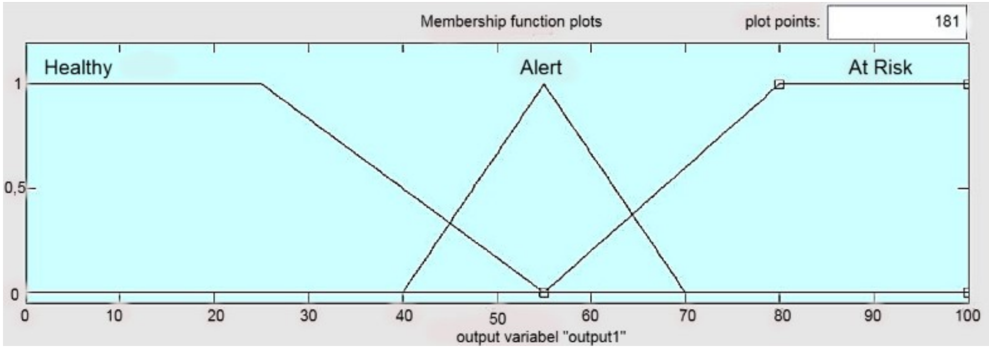

Figure 8. Membership Function of Heart Health Status

Based on Table 5, the value of heart health status is grouped into three fuzzy categories, namely healthy, alert, and at risk. The membership function for each category is arranged based on the shape of the graph, up, triangle, and down.

$$\text{At Risk}(x)\begin{cases} 1 & ,x \leq 30 \\ \frac{50-x}{50-30} & ,30 < x < 50 \\ 0 & ,x \geq 50 \end{cases} \tag{14}$$

$$\mu\text{Healthy}(x)\begin{cases} 0 & ,x \leq 45 \\ \dfrac{x-65}{90-65} & ,65 < x < 90 \\ 1 & ,x \geq 90 \end{cases} \tag{15}$$

$$\mu\text{Alert}(x)\begin{cases} 0\,;\ x \leq 45 \text{ or } x \geq 70 \\ \frac{x-45}{60-45} & ;45 < x \leq 60 \\ \frac{70-x}{70-60} & ;60 < x < 70 \\ 1 & ;x = 60 \end{cases} \tag{16}$$

This research focuses on the data processing involved in an Arduino-based heart rate monitoring system that utilizes MAX30102 series pulse sensors and MLX90614 sensors. The processed data includes heart rate, body temperature, and age, which are analyzed using Mamdani fuzzy logic to generate health condition information that serves as the basis for decision-making.

The input data for the heart rate monitoring system is categorized into fuzzy variables, as shown in Table 1. Heart rate is classified into three categories: bradycardia, normal, and high; body temperature is divided into low, normal, and high; and age is segmented into young, adult, and elderly. These variables are transformed into fuzzy membership functions, illustrated in Tables 2, 3, and 4, which are essential for interpreting the input data and determining the user's health status.

Despite the system's demonstrated functionality, a deeper analysis of the results is warranted. The average error rate of 16.3% for the MAX30102 pulse sensor, categorized as moderate, raises concerns about the reliability of heart rate measurements. Such a level of error could significantly impact the system's effectiveness, especially in clinical settings where precise monitoring is crucial. In contrast, the MLX90614 body temperature sensor exhibited a lower error rate of 3.95%, classified as low. However, it is important to consider potential sources of these errors, including sensor calibration, environmental influences, and user variability, which could affect the accuracy of the readings.

The discussion would also benefit from a comparative analysis with previous research. For instance, studies that report lower error rates or employ different methodologies could provide valuable insights into how this system could be improved or adapted. Research conducted by Ngabi et al. (2022), which achieved lower error rates in heart rate monitoring, underscores the need for further refinement in sensor technology and data processing methods.

Moreover, the limitations of the current study must be acknowledged. The small sample size of six respondents restricts the generalizability of the findings, and the lack of diverse demographic representation may not accurately reflect the broader population's health conditions. Future research should aim to include a larger and more varied sample to validate the system's effectiveness across different age groups and health statuses.

In summary, while the functionality of the system is established, a more comprehensive discussion that includes critical analysis of the results, reflections on potential errors and limitations, and comparisons with existing literature is essential. This approach will not only strengthen the argument but also provide a clearer pathway for future improvements and applications of the Arduino-based heart rate monitoring system. By addressing these aspects, the research can contribute more meaningfully to the field of health monitoring technology, ensuring that the system is not only functional but also reliable and applicable in real-world scenarios.

4.1.1. Fuzzy Set Formation

Based on the general form contained in the basic fuzzy Mamdani rules and the number of fuzzy sets from each input variable, 27 possible fuzzy rules can be formed. The rules can be seen in the following Table 6.

Table 6. Fuzzy Rules

No	Variable			
	Input			Output
	Heart Rate	Body Temperature	Age	Heart Health Status
R1	Normal	Normal	Young	Healthy
R2	Normal	Normal	Adult	Healthy
R3	Normal	Normal	Elderly	Alert
R4	High	High	Young	Alert
R5	High	High	Adult	At risk
R6	High	High	Elderly	At risk
R7	Bradycardia	Low	Young	Alert
R8	Bradycardia	Low	Adults	Alert
R9	Bradycardia	Low	Elderly	At Risk
R10	Normal	High	Young	Alert
R11	Normal	High	Adults	Alert
R12	Normal	High	Elderly	At risk
R13	High	Normal	Young	Alert
R14	High	Normal	Adult	Alert
R15	High	Normal	Elderly	At risk
R16	Bradycardia	Normal	Young	Alert
R17	Bradycardia	Normal	Adults	Alert
R18	Bradycardia	Normal	Elderly	At Risk
R19	Normal	Low	Young	Healthy
R20	Normal	Low	Adult	Alert
R21	Normal	Low	Elderly	Alert
R22	High	Low	Young	Alert
R23	High	Low	Adult	Alert
R24	High	Low	Elderly	At Risk
R25	Bradycardia	High	Young	Alert
R26	Bradycardia	High	Adults	At Risk
R27	Bradycardia	High	Elderly	At risk

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Each membership degree that has been calculated is processed into 27 fuzzy rules that have been made before. To determine the α-predicate value, the variables are combined using the AND operator. The inference function must know the rules used in the system to get the value that will be used in the defuzzification process.

1. $\alpha - [R1] = \min(\mu normal[70] \cap \mu normal[36,3] \cap \mu young[23]) = \min(0.5 \cap 0,6 \cap 0,4) = 0.4$

   Rule implication function, Zn = Zmax - α-predicate X (Zmax- Zmin) = 90-0.4 X (90-65) = 90

2. $\alpha - [R2] = \min(\mu normal[70] \cap \mu normal[36,3] \cap \mu adult[39]) = \min(0.5 \cap 0,6 \cap 0,6) = 0.5$

   Rule implication function, Zn = Zmax - α-predicate X (Zmax- Zmin) = 90-0.5 X (90-65) = 77.5

3. $\alpha \quad [R3] = \min(\mu normal[70] \cap \mu normal[36,3] \cap \mu elderly[60] = \min(0.5 \cap 0,6 \cap 1) = 0.5$

   Rule implication function, Zn = Zmax - α-predicaten X (Zmax- Zmin) = 60-0.5 X (60-45) = 52.5

   ....

4. $\alpha - [R27] = \min(\mu bradycardia[50] \cap \mu high[39] \cap \mu elderly[60]) = \min(0.16 \cap 0,6 \cap 1) = 0.16$

   Rule implication function, Zn = Zmax - α-predicate X (Zmax- Zmin) = 50-0.16 X (50-30) = 46.8

Next, calculate the defuzzification value with the weighted average (WA) formula:

$$WA = \frac{(a_1 * z_n) + a_1 * z_n}{a_1 * z_n} \tag{17}$$

$$WA = \frac{513,088}{9,44} = 54.35 \tag{18}$$

4.2. Dissolution (Tool System Testing)

Testing is carried out to determine whether the system that has been designed functions according to predetermined parameters. The purpose of this test is to ensure that the monitoring system is able to read data from sensors accurately, process the data using the Mamdani fuzzy logic method, and display real-time diagnosis results through the laptop monitor screen.

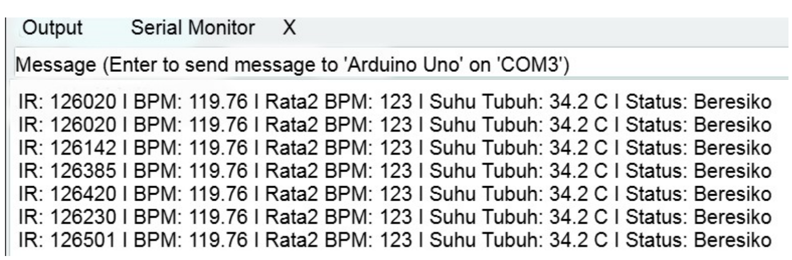


Figure 9. At Risk Status

In conditions where the heart rate is in the high category at 123 BPM, the body temperature is low at 34.7°C, and the user is in the young age category at 24 years old, the system will classify this condition as an at-risk status. In this situation, the system will provide a notification on the laptop monitor screen for the user (refer to the Figure 9).

In a condition where the heart rate is in the normal category of 74 BPM, the body temperature is low at 34.5°C, and the user is in the young age category of 22 years old, the system will classify this situation as an alert status. In this situation, the system will provide a notification on the laptop monitor screen for the user (refer to the Figure 10).

```
Output        Serial Monitor    X
Message (Enter to send message to 'Arduino Uno' on 'COM3')
IR: 105990 | BPM: 97.24 | Rata2 BPM: 76 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 105998 | BPM: 97.24 | Rata2 BPM: 76 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 106009 | BPM: 97.24 | Rata2 BPM: 76 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 106014 | BPM: 97.24 | Rata2 BPM: 76 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 106012 | BPM: 97.24 | Rata2 BPM: 76 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 105979 | BPM: 97.24 | Rata2 BPM: 76 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 105920 | BPM: 97.24 | Rata2 BPM: 76 | Suhu Tubuh: 34.5 C | Status: Waspada
```

Figure 10. Alert Status for 34.5 Celcius

When the system detects the heart rate is in the bradycardia category, which is around 40 BPM, the body temperature is detected to be low, which is around 33.7°C, and the adult's age is 33 years old, the system will classify the condition as an alert status. In this situation, the system will provide a notification on the laptop monitor screen for the user (refer to the Figure 11).

```
Output        Serial Monitor    X
Message (Enter to send message to 'Arduino Uno' on 'COM3')
IR: 94842 | BPM: 29.27 | Rata2 BPM: 40 | Suhu Tubuh: 33.7 C | Status: Waspada
IR: 94845 | BPM: 29.27 | Rata2 BPM: 40 | Suhu Tubuh: 33.7 C | Status: Waspada
IR: 94843 | BPM: 29.27 | Rata2 BPM: 40 | Suhu Tubuh: 33.7 C | Status: Waspada
IR: 94841 | BPM: 29.27 | Rata2 BPM: 40 | Suhu Tubuh: 33.7 C | Status: Waspada
IR: 94842 | BPM: 29.27 | Rata2 BPM: 40 | Suhu Tubuh: 33.7 C | Status: Waspada
IR: 94843 | BPM: 29.27 | Rata2 BPM: 40 | Suhu Tubuh: 33.7 C | Status: Waspada
IR: 94842 | BPM: 29.27 | Rata2 BPM: 40 | Suhu Tubuh: 33.7 C | Status: Waspada
```

Figure 11. Alert Status for 37.7 Celcius

When the system detects the heart rate is in the Normal category, which is around 74 BPM, the body temperature is detected to be low, which is around 34.5°C, and the adult's age is 27 years old, the system will classify the condition as alert status. In this situation, the system will provide a notification on the laptop monitor screen for the user (refer to the Figure 12).

```
Output        Serial Monitor    X
Message (Enter to send message to 'Arduino Uno' on 'COM3')
IR: 105921 | BPM: 73.38 | Rata2 BPM: 74 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 105918 | BPM: 73.38 | Rata2 BPM: 74 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 105920 | BPM: 73.38 | Rata2 BPM: 74 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 105946 | BPM: 73.38 | Rata2 BPM: 74 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 105992 | BPM: 73.38 | Rata2 BPM: 74 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 105951 | BPM: 73.38 | Rata2 BPM: 74 | Suhu Tubuh: 34.5 C | Status: Waspada
IR: 105981 | BPM: 73.38 | Rata2 BPM: 74 | Suhu Tubuh: 34.5 C | Status: Waspada
```

Figure 12. Alert Status for 34.5 Celcius

In conditions where the heart rate is in the normal category of 76 BPM, the body temperature is normal at 36.2°C, and the user is in the elderly age category of 47 years old, the system will classify this condition as a healthy status. In this situation, the system will provide a notification on the laptop monitor screen for the user (refer to the Figure 13).

```
Output        Serial Monitor    X
Message (Enter to send message to 'Arduino Uno' on 'COM3')
IR: 69001 I BPM: 68.10 I Rata2 BPM: 40 I Suhu Tubuh: 36.7 C I Status: Sehat
IR: 69008 I BPM: 68.10 I Rata2 BPM: 40 I Suhu Tubuh: 36.7 C I Status: Sehat
IR: 69052 I BPM: 68.10 I Rata2 BPM: 40 I Suhu Tubuh: 36.7 C I Status: Sehat
IR: 69001 I BPM: 68.10 I Rata2 BPM: 40 I Suhu Tubuh: 36.7 C I Status: Sehat
IR: 69069 I BPM: 68.10 I Rata2 BPM: 40 I Suhu Tubuh: 36.7 C I Status: Sehat
IR: 70149 I BPM: 68.10 I Rata2 BPM: 40 I Suhu Tubuh: 36.7 C I Status: Sehat
IR: 69001 I BPM: 68.10 I Rata2 BPM: 40 I Suhu Tubuh: 36.7 C I Status: Sehat
```

Figure 13. Healthy Status

In a condition where the heart rate is in the normal category at 95 BPM, the body temperature is low at 34.8°C, and the user is in the elderly age category at 60 years old, the system will classify this situation as an at-risk status. In this situation, the system will provide a notification on the laptop monitor screen for the user (refer to the Figure 14).

```
Output        Serial Monitor    X
Message (Enter to send message to 'Arduino Uno' on 'COM3')
IR: 103951 I BPM: 97.72 I Rata2 BPM: 95 I Suhu Tubuh: 34.7 C I Status: Beresiko
IR: 103948 I BPM: 97.72 I Rata2 BPM: 95 I Suhu Tubuh: 34.7 C I Status: Beresiko
IR: 103960 I BPM: 97.72 I Rata2 BPM: 95 I Suhu Tubuh: 34.7 C I Status: Beresiko
IR: 104001 I BPM: 97.72 I Rata2 BPM: 95 I Suhu Tubuh: 34.7 C I Status: Beresiko
IR: 104019 I BPM: 97.72 I Rata2 BPM: 95 I Suhu Tubuh: 34.7 C I Status: Beresiko
IR: 104029 I BPM: 97.72 I Rata2 BPM: 95 I Suhu Tubuh: 34.7 C I Status: Beresiko
IR: 104022 I BPM: 97.72 I Rata2 BPM: 95 I Suhu Tubuh: 34.7 C I Status: Beresiko
```

Figure 14. Status at Risk

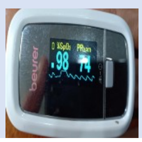
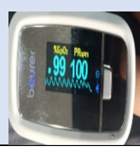
Overall, the test results prove that the designed system has been able to fulfill the objectives of the research, namely creating a simple health monitoring tool that can identify the user's condition automatically based on heart rate, body temperature, and age data. With the support of the Mamdani fuzzy logic method, this system is proven to be able to provide classification results that are logical and by real conditions. This shows that the Arduino-based system approach with pulse and body temperature sensors has the potential to continue to be developed as an independent health monitoring tool, especially at the individual or household level, although it still requires further improvement in terms of accuracy, stability, and comfort of use.

4.2.1. Oximetry Testing

Sensor testing is done by comparing oximetry data with data obtained from MAX30102 series pulse sensors. The test location was carried out at the Haris Success Doctor Practice Clinic located on Jln. Lembaga No.2, Tanjung Rejo, Kecamatan Percut Sei Tuan, Kabupaten Deli Serdang. The MAX30102 series pulse sensor is used as input to read the heart rate (BPM), and the resulting output must match the actual heart rate of the individual. Therefore, testing is needed to verify the accuracy of the MAX30102 series pulse sensor using an oximeter, so that the error value of the MAX30102 series pulse sensor can be known accurately. To test the MAX30102 series pulse sensor error against the oximeter, the following formula is used:

$$\%\ \text{Error rate} = (((\text{BPM Oxymeter} - \text{pulse sensor MAX30102 series}) : \text{BPM Oxymeter})) \times 100\% \qquad (17)$$

Table 7. Oximeter Testing

No	Name	Oximeter Result Picture (BPM)	MAX30102 Sensor Result Image (BPM)	Age (Year)	Result of the oximeter (BPM)	Result from MAX30102 sensor (BPM)	Error rate (%)
1	Rudi Kurniawan		Rata2 BPM: 123 Rata2 BPM: 123 Rata2 BPM: 123	24	105	123	17.1
2	Ardiansyah		Rata2 BPM: 76 Rata2 BPM: 76 Rata2 BPM: 76	22	83	76	8.4
3	Lara Santi		Rata2 BPM: 40 Rata2 BPM: 40 Rata2 BPM: 40	33	88	40	85.5
4	Sudarsono		Rata2 BPM: 74 Rata2 BPM: 74 Rata2 BPM: 74	27	74	74	0
5	Sri Novita		Rata2 BPM: 40 Rata2 BPM: 40 Rata2 BPM: 40	45	92	76	17.3
6	Sugirah		Rata2 BPM: 95 Rata2 BPM: 95 Rata2 BPM: 95	60	100	95	0.5
					Average Error Rate =		**16.3**

It is found that the percentage of the error rate is 16.3%, including in the moderate category, and then the accuracy value can be calculated to determine the percentage of accuracy. The accuracy value can be calculated through the equation.

$$Accuracy\ Value = 100\% - Average\ Value\ of\ Error\ Rate \quad (18)$$

$$Accuracy\ Value = 100\% - 16.3\% = 0.837\% \quad (19)$$

So, the level of accuracy obtained from the test is 0.837%. The difference in the oximeter values displayed in Table 7 can be caused by variations in the tolerance of the components used.

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4.2.2. Temperature Testing

Sensor testing is done by comparing temperature data with data obtained from the MLX90614 sensor. The test location was carried out at the Haris Success Doctor Practice Clinic located on Jln. Lembaga No.2, Tanjung Rejo, Kecamatan Percut Sei Tuan, Kabupaten Deli Serdang. The MLX90614 sensor is used as an input to read body temperature (°C), and the resulting output must match the actual body temperature of the individual. Therefore, testing is needed to verify the accuracy of the MLX90614 sensor using temperature, so that the error value of the MLX90614 sensor is accurately known. To test the MLX90614 sensor error against temperature, the following formula is used:

% Error rate = ((Temperature - MLX90614 Sensor) : Temperature)) X 100% (20)

Table 8. Temperature Testing

No.	Name	Thermometer Result Image (°C)	MLX90614 Sensor Result Image (°C)	Age (Year)	Result of Thermo (°C)	Result of MLX90614 Sensor (°C)	Error rate (%)
1	Rudi Kurniawan		Suhu Tubuh: 34.2 C Suhu Tubuh: 34.2 C Suhu Tubuh: 34.2 C	24	35.9	34.3	4.5
2	Ardiansyah		Suhu Tubuh: 34.5 C Suhu Tubuh: 34.5 C Suhu Tubuh: 34.5 C	22	36.3	34.5	4.9
3	Lara Santi		Suhu Tubuh: 33.7 C Suhu Tubuh: 33.7 C Suhu Tubuh: 33.7 C	33	34.9	33.7	3.4
4	Sudarsono		Suhu Tubuh: 34.5 C Suhu Tubuh: 34.5 C Suhu Tubuh: 34.5 C	27	35.3	34.5	2.2
5	Sri Novita		Suhu Tubuh: 36.7 C Suhu Tubuh: 36.7 C Suhu Tubuh: 36.7 C	45	36.5	36.7	5.4
6	Sugirah		Suhu Tubuh: 34.7 C Suhu Tubuh: 34.7 C Suhu Tubuh: 34.7 C	60	36.0	34.8	3.3
					Average Error Rate =		**3.95**

It is found that the percentage of the error rate is 3.95%, including in the low category, then the accuracy value can be calculated to determine the percentage of table accuracy. The accuracy value can be calculated through the equation.

Accuracy Value = 100% - Average Value of Error Rate (21)

Accuracy Value = 100% - 3.95% = 0.960% (22)

So, the level of accuracy obtained from the test is 0.960%. The difference in temperature values displayed in Table 8 can be caused by variations in the tolerance of the components used.

4.3. Applicability and Interest to the Field

The Arduino-based heart rate monitoring system developed in this research has significant applicability and relevance beyond the specific case presented. As heart disease remains a leading cause of mortality worldwide, the need for accessible and cost-effective health monitoring solutions is paramount. This system not only provides a practical tool for individuals to monitor their heart health at home but also serves as a valuable educational resource for students and professionals in health technology and biomedical engineering fields.

The integration of Mamdani fuzzy logic into the system enhances its adaptability and accuracy in assessing health conditions, making it a relevant model for future research and development in health monitoring technologies. The findings from this study can inform the design of similar systems that incorporate additional health metrics, such as oxygen saturation and respiratory rate, thereby broadening the scope of personal health monitoring.

Moreover, the system's low-cost and portable nature makes it suitable for use in low-resource settings, where access to advanced medical equipment may be limited. This aligns with global health initiatives aimed at improving health outcomes through technology, particularly in underserved communities.

4.4. Original Contribution to Open and Distributed Learning

While the research does not directly contribute to open and distributed learning, it does provide a foundation for educational initiatives that can leverage the Arduino-based system for teaching purposes. The hands-on experience of building and programming such a system can enhance learning in various disciplines, including computer science, electronics, and health sciences.

Future developments could focus on creating educational modules or workshops that utilize this system, allowing students to engage with real-world applications of technology in health monitoring. By fostering an interactive learning environment, this research can inspire innovation and critical thinking among learners, ultimately contributing to the advancement of health technology education.

In summary, while the direct contributions to open and distributed learning may be limited, the broader implications of this research in health monitoring technology and its potential for educational applications are significant and warrant further exploration.

5. Conclusion

This study successfully developed an Arduino Uno-based heart rate monitoring system using the MAX30102 pulse sensor and MLX90614 body temperature sensor, with data processing implemented through the Mamdani fuzzy logic method. The system can monitor health conditions in real-time by considering three variables: heart rate, body temperature, and age and classifying the results into three categories: healthy, alert, and at risk. This fuzzy-based approach enables the system to handle biological data that is uncertain and variable, offering a more flexible and human-like reasoning pattern compared to conventional binary logic methods. The application of 27 fuzzy rules and three fuzzy sets for each input variable allows more adaptive decision-making across diverse user conditions. Test results show an average error rate of 16.3% for the MAX30102 pulse sensor (medium category) and 3.95% for the MLX90614 temperature sensor (low category), which is acceptable for a prototype stage. However, the study has limitations, including the small number of test samples and the moderate accuracy of the pulse sensor. Future research should focus on increasing the number of samples for more robust validation, improving sensor accuracy, and integrating the system with cloud-based platforms or IoT devices for broader accessibility and real-time remote monitoring. The proposed system demonstrates the potential for an affordable, portable, and user-friendly tool for early heart health monitoring, which could complement conventional clinical devices and support preventive healthcare at the household level.

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