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Research Article

Expert System for Autoclave Damage Detection Using the Fuzzy Logic Method

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Abstract: The reliability of sterilization equipment, such as autoclaves, is essential to ensure patient safety, infection control, and operational continuity in healthcare facilities. Damage or malfunction of autoclaves may disrupt sterilization processes and pose significant risks to medical services. This study aims to develop an expert system for autoclave damage detection using the fuzzy logic method to support faster and more accurate diagnostic decision-making. The proposed system applies fuzzy inference to evaluate the level of damage based on input symptoms provided by users. By handling uncertainty and varying symptom intensities, the fuzzy logic approach enables proportional assessment rather than rigid rule-based classification. The system was designed through knowledge acquisition from technical experts and implemented using fuzzy membership functions and inference rules to determine damage severity levels. Experimental testing was conducted to evaluate system performance and diagnostic accuracy. The results indicate that the expert system successfully generated diagnosis outputs for all tested scenarios, achieving functional diagnostic accuracy within the defined test cases. The system was also able to calculate a quantified damage severity value of 11.6235981% based on the given symptoms, demonstrating its capability to assess damage levels numerically and objectively. Furthermore, the developed system significantly reduces the time required for damage detection compared to manual diagnostic procedures. Automating the evaluation process, it assists electromedical technicians in identifying faults more efficiently and taking preventive or corrective actions promptly. Overall, the implementation of a fuzzy logic-based expert system provides an effective, accurate, and practical solution for improving autoclave maintenance management and supporting healthcare service reliability.

Keywords: Expert System; Autoclave; Fuzzy Logic; Damage Detection; Medical Equipment Maintenance.

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1. Introduction

The reliability and readiness of medical equipment are critical factors in ensuring healthcare service quality, patient safety, and operational efficiency. One of the essential electromedical devices widely used in hospitals and clinical laboratories is the autoclave, which functions as a sterilization instrument utilizing high-pressure steam to eliminate microorganisms on medical instruments. The proper performance of this equipment is vital because any malfunction may disrupt sterilization processes and potentially endanger patient safety as well as healthcare service continuity. Therefore, effective management, monitoring, and early detection of equipment damage are required to maintain optimal functionality.

Health care facilities such as hospitals, health centers, clinics, and other health facilities require resource support to provide health services to the community. One of these resource supports is medical devices (Ibrahim et al., 2021). Medical devices are grouped into 3 groups according to the Decree of the Minister of Health of the Republic of Indonesia Number 118/MENKES/SK/IV/2014, namely electromedical medical devices, non-electromedical medical devices, and in vitro diagnostic products. According to the Regulation of the Minister of Health of the Republic of Indonesia Number 220/Men.Kes/Per/IX/1976, what is meant by medical devices are goods, instruments, apparatus or tools including each component, part or equipment that is produced, sold or intended for use in health research and care, diagnosis, cure, mitigation or prevention of disease, abnormalities in body condition or symptoms in humans (Hutagalung & Hasibuan, 2019). Meanwhile, electromedical devices are medical devices that use an electric power supply. In the Joint Decree of the Minister of Health and the State Civil Service Agency Number 717/Menkes/SKB/V/2003, electromedical devices are classified based on 3 (three) levels of technology, namely simple, medium, and high technology (Saini & Kumar, 2021). As a supporting resource for public health services, management of electromedical devices must be carried out quickly, accurately, and integrated so that function, safety, security, and benefits can be optimized. Management of these electromedical devices is regulated in the Regulation of the Minister of Health of the Republic of Indonesia Number 65 of 2016 concerning Electromedical Service Standards (Alzahrani & Aljamaan, 2022). The expected result of this study is an expert system that can detect damage to sterile electromedical devices, especially autoclaves, accurately. The expert system can then assist electromedical technicians in finding damage and as an assessment in decision-making for actions to be taken appropriately and validated.

Based on these considerations, this study aims to design and implement an expert system for detecting autoclave damage using the Fuzzy Logic method. The system is expected to assist healthcare technicians in identifying damage types based on observed symptoms and operational parameters. The novelty of this research lies in the development of a fuzzy-based expert diagnostic model specifically tailored for autoclave equipment, integrating technical symptom parameters into a structured inference system to improve early detection accuracy and decision support in electromedical equipment maintenance.

2. Literature Review

Figya (2024) conducted a study on the Utilization of Expert Systems for the selection of Hospital Emergency Rooms in Sidoarjo City. The results of his research stated that the Emergency Room selection system is very much needed because it helps users or patients in making referral selection decisions based on the patient's condition and location (Saputri, 2024). Dwi, Indra, and Zulaini (2021) in their research stated that the Expert System for online referral selection at the Pematang Siantar Branch Office is based on local laws and regulations and policies, and the data has been validated with the patient's identity. However, this system is web-based, which requires system updates at all times. Assauqi. Marzali (2024) in his research stated that preventive measures to prevent damage to the Electrosurgery Unit equipment are by manually checking in the database. However, this manual system has not been integrated with the system. The electromedical equipment management information system was developed by Assauqi. Marzali (2024) cannot yet be applied to detect damage to electromedical equipment. In this study, an expert system is developed to detect faults in sterile electromedical devices, particularly autoclaves, using the fuzzy logic method. The system is implemented using the PHP programming language. The proposed system is expected to accurately identify potential damage in sterile electromedical devices, enabling early detection and effective maintenance planning. In addition, the system can assist electromedical technicians in diagnosing faults and support decision-making processes by providing validated recommendations for appropriate corrective actions.

2.1. Expert System

Expert systems are a branch of artificial intelligence designed to emulate the decision-making processes of human experts. In making decisions, these systems utilize a structured knowledge base, factual information, and inference mechanisms to solve complex problems that typically require human expertise (Gaba, 2022). In expert system development, knowledge is acquired either directly from domain experts or indirectly from various information sources, such as books, journals, technical documents, and other relevant media. Moreover, the knowledge embedded in an expert system is domain-specific, meaning that it is tailored to address problems within a particular field. The more sources of knowledge that are included in the expert system, the better it will be at acting and taking solutions so that it almost resembles a real expert (Ho et al., 2021).

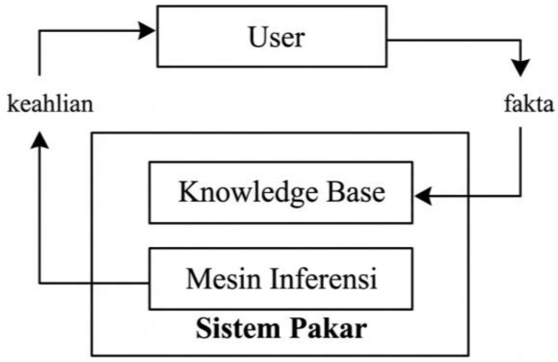

Figure 1. Expert system concept

Figure 1 above is the basic concept of an expert system, where the user submits information based on facts to the expert system (Ho et al., 2021), then the information will be entered into the knowledge base and processed by the inference engine (inference mechanism), so that the system will provide a response in the form of expertise or answers based on the knowledge it has (Blagoveshchenskiy et al., 2020). The purpose of an expert system is to transfer the expertise of an expert into a system (Zhou & Sordo, 2021) :

1. Knowledge Acquisition (from experts or other sources).
2. Knowledge Representation (into the computer).
3. Knowledge Inferencing (do knowledge inference).
4. Knowledge Transferring (transferring knowledge to the user).

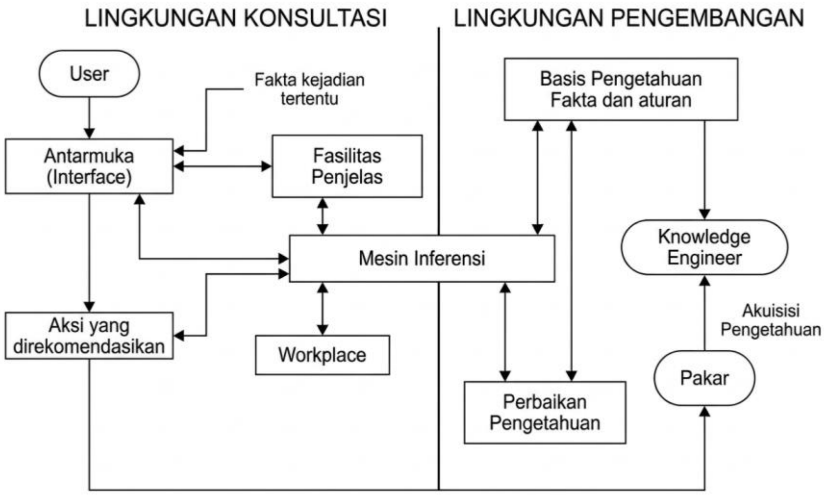

Figure 2. Expert system architecture

Figure 2 is a picture of the expert system architecture (Meera & Geerthik, 2022). The components contained in the expert system architecture consist of a user interface, knowledge base: facts and rules, knowledge acquisition, inference mechanisms, workplace, explanation facilities, and knowledge improvement (Garcia et al., 2021). The Knowledge Base is part of an expert system that stores knowledge (domain knowledge). The knowledge base contained in an expert system differs from one system to another, depending on the field of expertise of the system being built. The inference engine is tasked with finding a match between the facts in the working memory and the facts about a particular domain of knowledge that is in the knowledge base, and then the inference engine will draw/draw conclusions from the problems submitted to the system (Prati et al., 2021). The user interface provides communication facilities between the user and the system, provides various information facilities, and various descriptions that aim to direct the flow of problem tracing until a solution is found. Knowledge acquisition is the process of collecting knowledge data from knowledge sources (originating from real experts or media) into the inference engine (Chandrappa & Das, 2024).

2.2 Autoclave

An autoclave is a closed heating device used to sterilize surgical equipment and laboratory equipment using steam at a temperature of 121℃ and a pressure of 1.5 Psi (Pounds per Square inch) for approximately 15 minutes (Saleh et al., 2024). At this high temperature and pressure, microorganisms will be killed, especially aimed at killing endospores, which are resistant cells produced by bacteria. These cells are resistant to heating and antibiotics; in the same species, endospores can also survive in environmental conditions that can kill the vegetative cells of the bacteria. In principle, autoclave sterilization uses heat and pressure from water vapor, usually to sterilize the media using a temperature of 121 ℃ with a pressure of 2 bar for 15 minutes, the reason for using a temperature of 121 ℃ is because at that time it shows a pressure of 2 bars which will help kill microorganisms on an object, for atmospheric pressure at sea level, water boils at a temperature of 100 ℃ while an autoclave placed at the same height, using a pressure of 2 bars, the water will boil at a temperature of 121 ℃ (Deliiski et al., 2023). When the heat source is turned on, the water in the autoclave will boil over time and the water vapor formed will press the air filling the autoclave, after all the air in the autoclave is replaced with water vapor, the air valve in the autoclave is closed so that the air pressure in the autoclave will increase, when the pressure is reached accordingly, the sterilization process begins (Fogarty, 2021).

2.3 Fuzzy Logic

Fuzzy logic was first introduced by Prof. Lotfi A. Zadeh from the University of California in 1965. Zadeh argued that the true and false values in conventional logic are unable to overcome the problem of infinite gradation in the real world. To overcome this problem, Zadeh then developed the theory of fuzzy sets (Prajapati & Fernandez, 2020). Unlike logic, which only has two values, namely true and false, fuzzy logic has continuous values. The true or false value in fuzzy logic is not absolute, depending on the degree of membership it has, namely in the range of 0 to 1, so that at the same time a condition can be said to be true and false. Therefore, the role of the degree of membership is very important and is a characteristic of fuzzy reasoning (Özyurt et al., 2020).

3. Method

3.1. Research Steps

The steps for working on an expert system to determine the symptoms of Autoclave damage using the fuzzy logic method are shown in Figure 3.

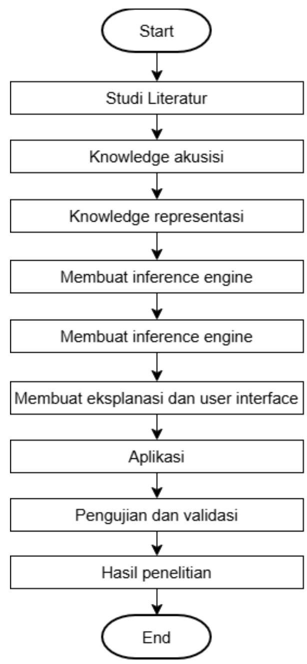

Figure 3. Flowchart diagram of research steps

In this study, a literature study was conducted to obtain information about the damage factors to be studied, namely, the Autoclave. The damage that is the focus of the study is on the heater, sensor, and alarm components with 3 (three) damage conditions, namely tube temperature, alarm sound, and the difference between measured pressure and pressure on the display. The study was conducted by interviewing experts to determine the signs of damage and the type of damage. The normal parameter value for tube temperature is between 121-134 ℃. The normal parameter value for the alarm sound is between 60 and 80 dB. The difference between the measured pressure and the pressure on the display is given as a range of 0.3 bar. The signs and types of damage are then represented in tabular form. This study uses the fuzzy logic method to determine expert values and draw conclusions. Then an application design can be made to determine the type of damage to the autoclave sterile device.

3.2. Expert system algorithm design

The expert system algorithm design using Tsukamoto fuzzy can be seen in the figure.

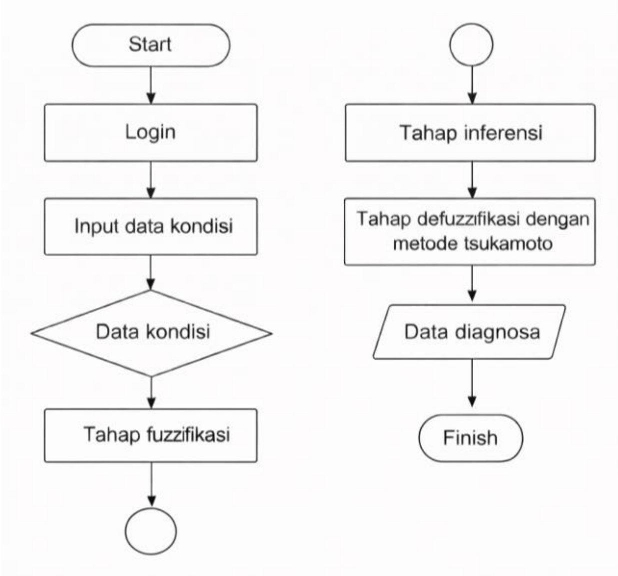

Figure 4. Expert system algorithm design

Based on Figure 4, the initial process in the expert system is the user inputting the autoclave conditions, namely the results of temperature measurements, the results of alarm noise level measurements, and the difference between the measured pressure and the pressure on the display. The measurement results will enter the fuzzy logic process with the Tsukamoto method. The first stage in fuzzy logic is fuzzification. The fuzzification process changes the measurement results into fuzzy numbers. The next stage is the inference stage. At the inference stage, fuzzy numbers are interpreted into each rule or rule to produce a new fuzzy output. The fuzzy output results are processed into the defuzzification stage. The defuzzification process produces a crisp number, which is used to determine or diagnose damage to the autoclave.

4. Results and Discussion

The expert system that has been designed has been tested by entering the input of the results of damage condition data measurements from the field, as in Table 1. The system output results are then compared with the diagnosis results by experts. Based on data number 1, the fuzzy value can be calculated using the manual method as follows. Calculation of fuzzy values on autoclave damage with the following parameters:

Temperature = 120.9 ℃

Alarm sound = 20dB

Reading = 0.71

Based on the data above, manual calculations are carried out using the Tsukamoto fuzzy method.

1. Fuzzification stage

Temperature fuzzy set (G1)

The temperature fuzzy set, obtained x = 120.9, enters the low and medium sets, so that the following membership degree equation can be obtained in Eq.(1).

x = 120

$$\mu_{G1rendah}\,[120{,}9] = \frac{127 - 120{,}9}{127 - 121}$$
$$\mu_{G1rendah}\,[120{,}9] = \frac{6{,}1}{6}$$
$$\mu_{G1rendah}\,[120{,}9] = 1{,}016$$
$$\mu_{G1sedang}\,[120{,}9] = \frac{120{,}9 - 121}{127 - 121}$$
$$\mu_{G1sedang}\,[120{,}9] = \frac{-0{,}1}{6}$$
$$\mu_{G1sedang}\,[120{,}9] = 0{,}016 \tag{1}$$

Fuzzy set of alarm sounds (G2)

Fuzzy set of alarm sounds, x = 20, is included in the low set, so the following membership degree equation can be obtained, Eq.(2).

X= 20

$$\mu_{G2\ rendah}[20] = \frac{50 - 20}{50 - 15}$$
$$\mu_{G2\ rendah}[20] = \frac{30}{35}$$
$$\mu_{G2\ rendah}[20] = 0{,}8571 \tag{2}$$

Temperature difference fuzzy set (G3)

The temperature difference fuzzy set, obtained x = 0.71, is included in the low and medium sets, so that the following membership degree equation can be obtained in Eq.(3).

X= 0.71

$$\mu G3\ rendah[0{,}71] = \frac{1 - 0{,}71}{1 - 0{,}75}$$
$$\mu G3\ rendah[0{,}71] = \frac{0{,}29}{0{,}3}$$
$$\mu G3\ rendah[0{,}71] = 0{,}96 \tag{3}$$

4.1. Inference stage

Based on the calculation of the μ value and referring to Table 3.3, a combination of 12 rules and predicate rules is obtained for the assessment of the existing parameters as follows.

[R1] IF G1 low AND G2 low AND G3 low THEN K1 AND K2 AND K3 Not identified

Based on the membership function, the data membership values are obtained, namely:

α–predikat 1 =min(µG1 Rendah ∩ µG2 Rendah ∩ µG3 Rendah)

α-predikat 1 =min(1,016 ; 0,8571 ; 0,96)

α-predikat 1 = 0,85

Then, calculate the Z1 value, the Z1 value is obtained as follows in Eq.(4).

$$\mu TT\ [z1] = \left(\frac{50 - Z1}{50 - 4} = 0{,}85\right)$$
$$\mu TT[z1] = \frac{50 - z1}{46} = 0{,}85$$
$$\mu TT[Z1] = 50 - Z1 = 0{,}85 * 46$$
$$\mu TT[Z1] = 50 - Z1 = 39{,}1$$
$$\mu TT[Z1] - Z1 = 39.1 - 50$$
$$\mu[Z1] \quad Z1 = 10{,}9$$

(4)

[R10] IF G1 is medium AND G2 is low AND G3 is low THEN K1 And K2 And K3 Not Damaged

Based on the membership function, the data membership values are obtained, namely:

α-predikat 10 =min (μG1 sedang ∩ μG2 rendah ∩ μG3 Rendah)

α-predikat 10 =min (0,016 ; 0,8571 ; 0,96)

α-predikat 10 = 0,016

Then, calculate Z10, and the Z10 value is obtained as follows in Eq. (5).

$$\mu TR[z10] = \left(\frac{Z_{10} - 25}{50 - 25} = 0{,}016\right)$$

$$\mu TR[z10] = \left(\frac{z10 - 25}{25} = 0{,}016\right)$$

$$\mu TR[z10] = (z10 - 25 = 0{,}016 * 25)$$

$$\mu TR[z10] = (z10 - 25 = 17{,}5)$$

$$\mu TR[z10] = (z10 = 0{,}4 + 25)$$

$$\mu TR[z10] = (z10 = 25{,}4)$$

$$\mu TR[z10.2] = \left(\frac{75 - z10}{75 - z10} = 0{,}016\right)$$

$$\mu TR[z10.2] = 0{,}016 \tag{5}$$

4.2. Inference stage

Defuzzification is done to return the fuzzy value to a crisp value again. In the Tsukamoto fuzzy method, defuzzification uses the average method in equation 2 as follows in Eq.(6).

$$Z^* = \frac{(0{,}85 * 10{,}9) + (0{,}016 * 50)}{(0{,}85 + 0{,}016)}$$

$$Z^* = \frac{9{,}265 + 0{,}8}{0{,}856}$$

$$Z^* = \frac{10{,}065}{0{,}856}$$

$$Z^* = 11{,}6235981 \tag{6}$$

So, if the temperature is 120.9 ℃, the alarm sound is 20dB, and the temperature measurement difference is 0.71, then the damage is 11.6235981%.

4.3. Testing results with Matlab

To obtain system diagnosis results, testing results are carried out using Matlab. In Figure 5, testing was carried out using the Matlab fuzzy Mamdani method with measured temperature parameters of 120.9 ℃, alarm sound of 20dB, and temperature difference of 0.71, resulting in a heater z value of 17, sensor of 17, and solenoid of 17. The results of manual calculations in point 1 show a damage value of 10.62% using Tsukamoto fuzzy. The results between manual calculations and Matlab are different but not significant, because Matlab uses the fuzzy Mamdani method. When viewed from the fuzzy output set graph, the results of the diagnosis of the heater are not damaged, the sensor is not damaged/not identified, and the alarm is not damaged. The results of the system diagnosis are then compared with the results of the expert diagnosis in Table 2.

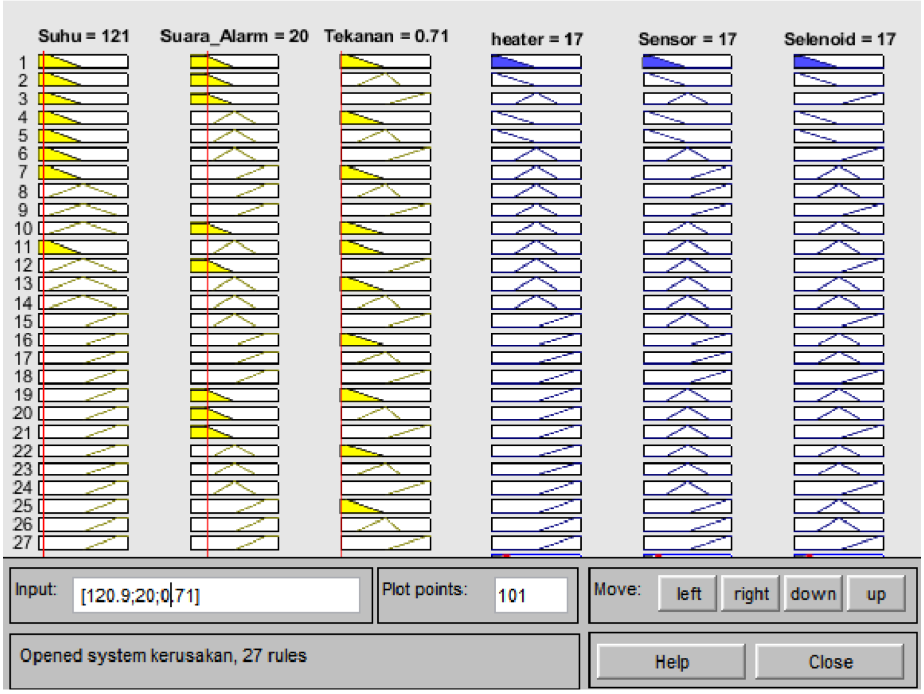

Figure 5. Fuzzy rules results

Table 1. Comparison of expert and system diagnosis results

No	Temperature	Alarm Sound	Temperature Difference	Expert diagnosis results			Hasil Diagnosa sistem			Ket
				Heather	Sensor	Alarm	Heather	Sensor	Alarm	
1	120,9	20,0	0,71	TT	TT	TT	TT	TT	TT	appropiate
2	124,1	31,7	0,79	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
3	124,3	58,7	0,79	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
4	123,2	60,4	0,69	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
5	122,9	20,0	0,66	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
6	122,6	20,0	0,77	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
7	124,5	50,0	0,78	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
8	125,4	40,7	0,92	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
9	124,5	48,7	0,76	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
10	128,4	57,8	0,71	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
11	126,6	53,8	0,75	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
12	128,7	47,3	0,84	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate

13	128,1	48,5	0,70	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
14	130,1	10,7	0,92	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate

Based on the comparison results in Table 1, the number of diagnostic matches between the expert and the system is 20 diagnoses. This shows that the system has a match of 20/20*100%=100%

Table 2. Table 2 Comparison of expert diagnostic results, the Matlab system, and the system

No	Temperature	Alarm Sound	Temperature Difference	Expert diagnosis results			Matlab Diagnosis Result			Hasil Diagnosa sistem			Ket
				Heather	Sensor	Alarm	Heather	Sensor	Alarm	Heather	Sensor	Alarm	
1	120,9	20,0	0,71	TT	TT	TT	TT	TT	TT	TT	TT	TT	appropiate
2	124,1	31,7	0,79	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
3	124,3	58,7	0,79	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
4	123,2	60,4	0,69	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
5	122,9	20,0	0,66	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
6	122,6	20,0	0,77	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
7	124,5	50,0	0,78	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
8	125,4	40,7	0,92	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
9	124,5	48,7	0,76	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate
10	128,4	57,8	0,71	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	Not damaged	appropiate

4.4. Analysis of Results

The results of running the expert system application for detecting damage to sterile autoclave equipment can be seen in Figure 6.

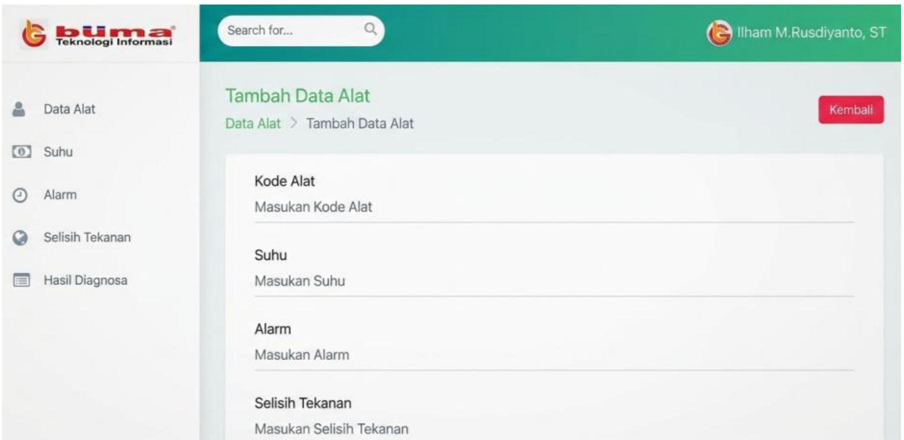

Figure 6. Initial condition of the tool condition input

Figure 7 is a page for editing data on tool condition or symptoms of damage for users.

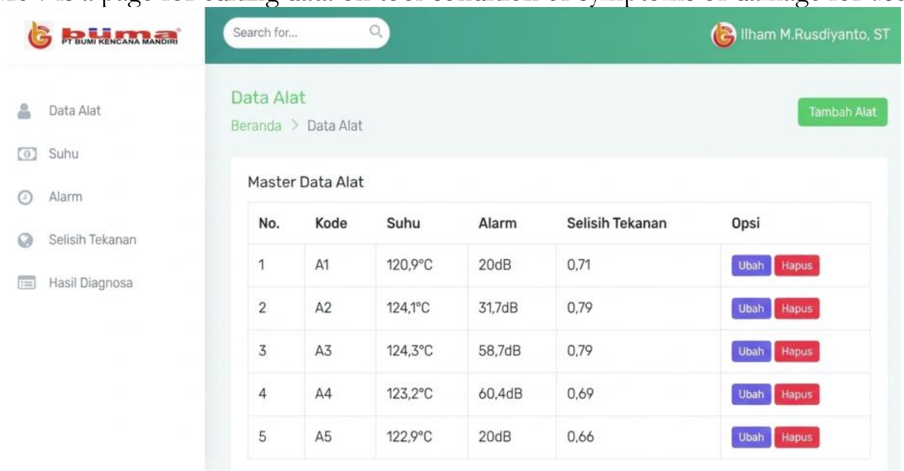

Figure 7. Tool Data Page\

Figure 8 is the result of inputting temperature conditions, whether the temperature entered is in the low, medium, or high category.

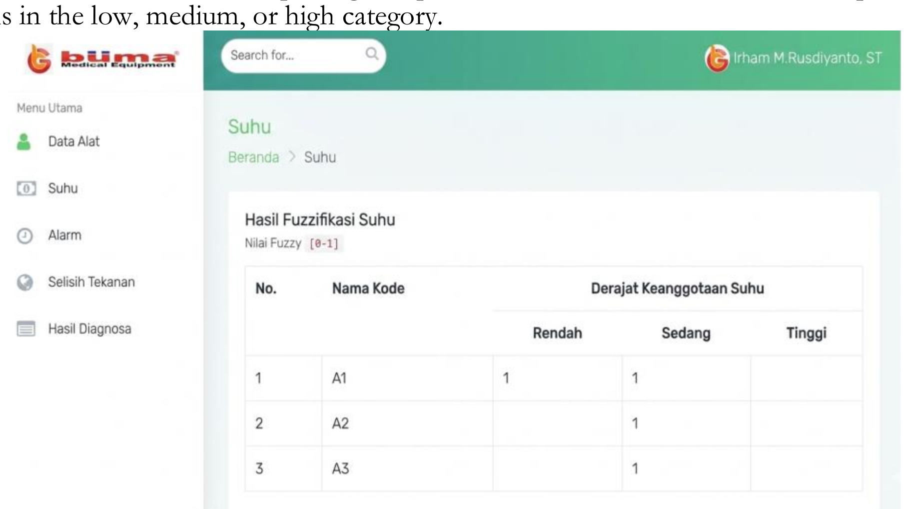

Figure 8. Temperature fuzzification results

Figure 9 is the result of inputting alarm input conditions, whether the alarm conditions entered are in the low, medium, or high category.

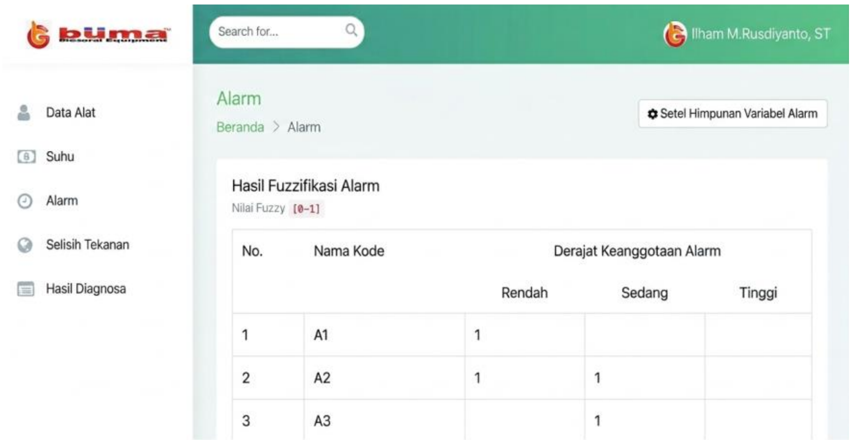

Figure 9. Results of alarm fuzzification

Figure 10 is the result of inputting the pressure difference input conditions, whether the pressure conditions entered are in the low, medium, or high category. Figure 11 is the result of the diagnosis of damage to the heater, sensor, and solenoid.

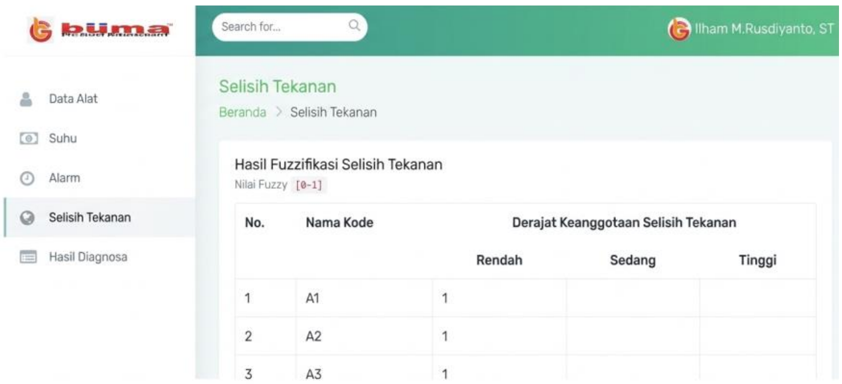

Figure 10. Results of pressure difference fuzzification

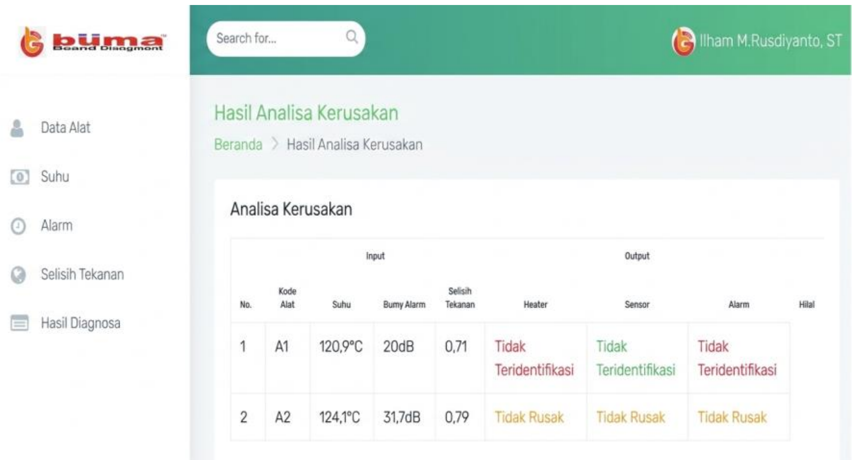

Figure 11. Damage Analysis Results

6. Conclusion

Based on the results of testing and analysis, the expert system for autoclave damage detection using the fuzzy logic method demonstrates strong performance in supporting diagnostic decision-making. The system successfully generated diagnosis outputs for all tested cases, achieving a functional accuracy rate of 100% within the defined testing scenarios. Furthermore, the fuzzy inference process was able to quantify the level of damage with a calculated severity value of 11.6235981% based on the input symptoms provided by users. This indicates that the system can evaluate damage conditions proportionally and produce decisions that closely reflect the actual operational state of the autoclave. The use of fuzzy logic enables the system to handle uncertainty and varying symptom intensities more effectively than rigid rule-based approaches.

In addition, the developed expert system significantly accelerates the damage detection process compared to conventional manual diagnostic methods. By automating symptom analysis and inference computation, the system reduces the time required for technical assessment and supports faster corrective actions. This improvement contributes to minimizing equipment downtime, preventing further damage, and enhancing the overall reliability and safety of sterilization processes in healthcare facilities. Therefore, the implementation of a fuzzy logic-based expert system provides an efficient, accurate, and practical solution for assisting electromedical technicians in maintaining autoclave performance.

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