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Design of stress detector with fuzzy logic method (GSR and heart rate parameters)

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ABSTRACT

Stress is a condition of tension that affects emotions, thought processes, and the physical or psychological state of humans due to pressure from within or from outside a person, which can interfere with activities that can cause various diseases. Therefore, a tool is made to detect stress levels so that a person can monitor their condition and prevent stress from getting more severe and detrimental to the health of the body and mind. The stress level detection tool is designed using a galvanic skin response (GSR) sensor to detect skin response through a person's sweat glands and a heart rate sensor to detect heart rate. Furthermore, the reading results will be processed by microcontroller and then the stress level decision will be made using the fuzzy logic method and will be classified into Relax, Anxiety, Calm, and Stress. Based on the test results, the GSR parameter has the highest accuracy of 99.78%, and the heart rate parameter has the highest accuracy of 99.63%.

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1. INTRODUCTION

The world health organization (WHO) states that around 450 million people experience stress [1]. Signs of human stress reactions include physical reactions, including increased heart rate, elevated blood pressure, and cold sweats (cold hands) [2]. Heart rate and galvanic skin response (GSR) are indicators of stress. Thus, abnormal values for heart rate are more than 100 bpm, and abnormal skin conductivity GSR values are more than 6 Siemens [3]. This could indicate that the person is under stress. Table 1 [4] shows the level of emotion state with GSR and heart rate values for each state. Prolonged stress can be fatal to health because it can cause various diseases and reduce body immunity. To avoid the impact caused by stress, we need a tool to detect stress levels in individuals, namely using heart rate and skin conductivity GSR measurement tools.

Previously, a human stress level detector was made with parameters of body temperature, skin moisture, blood pressure, and heart rate [5]. This tool used Atmega8535 as a data processor, LM35dz as a body temperature detector, MPX5050dp sensor as a heart rate and blood pressure detector, and aluminum foil is used as a detector for the skin resistance value of two fingers GSR. The results obtained from the measurements of each sensor will be compared with the tables for limiting human stress levels in young adults. From the results of this comparison, a decision will be obtained that displays the stress level in humans. The system testing results show that this human stress level detector can provide information about human stress levels with an average percent error of 3.5% on GSR measurements, 1.4% on temperature measurements, 11.76% on heart rate measurements, and 9.87% on blood pressure measurements. The tool that has been made can provide information about stress level conditions, but the results are inaccurate because the method used to determine the stress level is still manual. So, it is necessary to do further research to strengthen the research results by using a method.

Subsequent research made a person's psychological detection tool based on a computer-based heart rate [6]. This tool uses a heart rate sensor that is placed on the fingertip, then processed by the Arduino Uno. The data received by Arduino is forwarded through processing software to display output on a computer screen and can detect heartbeats when relaxed and emotional. Based on the test results, the relaxed state of the heart rate ranges from 60 to 70 beats per minute (BPM), and the test results in emotional conditions the heart rate ranges from 100 to 140 BPM. This tool can display the output results from the heart rate sensor on the laptop/computer monitor display. However, it has drawbacks, namely using only one parameter to detect a person's psychology and can only detect 2 conditions when a person is relaxed or emotional.

Based on the chronology above, the author will make an stress detection tool with the fuzzy logic method using the GSR sensor module to detect skin conductivity which is the skin resistance of two fingers and a heart rate sensor to detect a person's heart rate in BPM [7]–[9], besides that, it can display 4 stress levels experienced by a person namely stress (s=stressed), anxious (t=tense), calm (c=calm), and relaxed (r= relaxed) [10]. Then for stress levels, decision-makers will use the fuzzy logic method.

Fuzzy logic is an appropriate way to map the input space into an output space. Fuzzy logic uses language expressions to describe variable values [11]–[13]. Fuzzy logic works by using the degree of membership of a value which is then used to determine the results to be produced based on predetermined specifications. It has been mentioned before that fuzzy logic maps the input space to the output space. Between input and output, there is a black box that must map the input to the appropriate output.

Table 1. GSR and heart rate values of stress level [4]

Stress level	Parameters	
	GSR (Siemens)	Heart rate (BPM)
Relax	<2	60 – 70
Calm	2-4	70 – 90
Anxiety	4-6	90 – 100
Stress	>6	>100

2. METHOD

2.1. Fuzzy logic system

Based on the fuzzy logic block diagram in Figure 1, it can be explained that heart rate and GSR are inputs from the fuzzy system, fuzzification functions to convert heart rate and GSR values into membership functions. The heart rate membership function is divided into four membership functions: very slow, slow, fast, and very fast. In contrast, GSR is divided into four membership functions: very dry, dry, wet, and very wet. Then reasoning (inference machine) functions as an implication process in reasoning input values to determine output values as a form of decision-making through minimum reasoning. The basic rules in this fuzzy system are in the form of an IF–THEN relation, which consists of 16 rules [14]–[16]. In comparison, defuzzification is the process of changing the fuzzy output value into a firm output value, which will determine the stress level experienced by a person in the form of 4 conditions: relax, calm, anxiety, and stress.

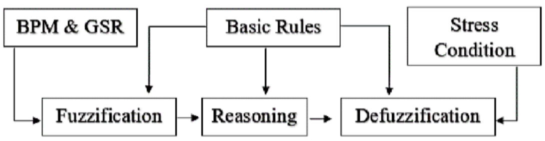
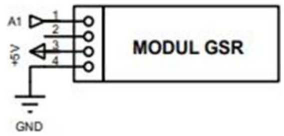


Figure 1. Diagram of fuzzy logic system

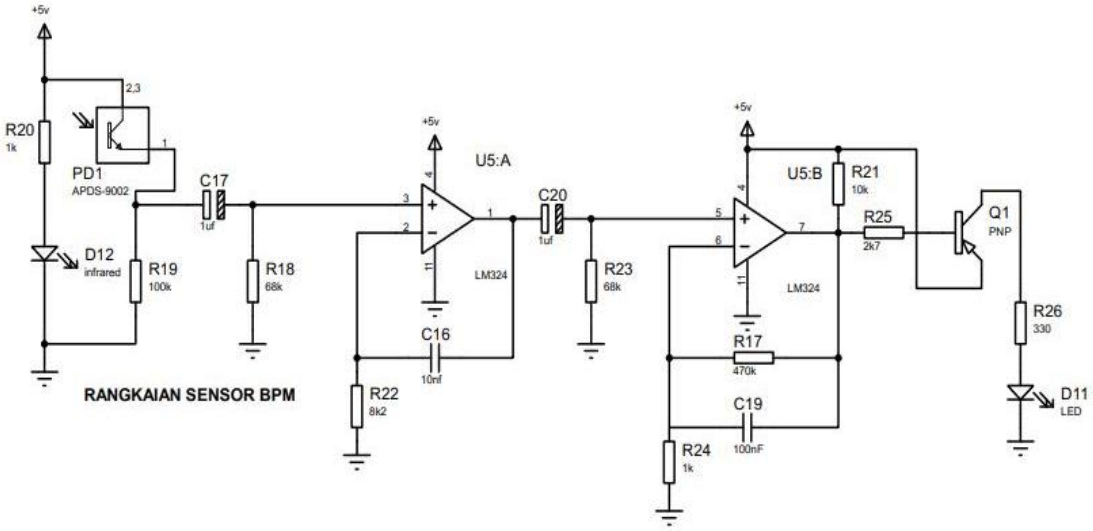
2.2. Hardware system (GSR and heart rate sensor circuit)

The hardware design of this stress detector is meticulously crafted to measure physiological signals that are indicative of stress, utilizing advanced sensor technologies. At the core of this system are two primary sensors: the heart rate sensor and the GSR sensor. The heart rate sensor, which uses infrared technology, detects the blood flow changes by emitting light into the finger and measuring the reflected light intensity through a phototransistor. This method allows for accurate detection of heart beats per minute BPM, which is a crucial indicator of stress. Alongside, the GSR sensor monitors the electrical conductance of the skin, which varies with sweat gland activity, thereby providing insights into the user's emotional and stress levels. These sensors work in tandem to capture the physiological data necessary for the fuzzy logic system to evaluate and classify the stress levels. The integration of these sensors within the hardware system ensures that the stress detection is both precise and responsive to real-time changes in the user's physiological state.

In Figure 2, we can see the hardware of system, it consists of Figure 2(a) the GSR sensor circuit [17] has an output in the form of an analog signal, namely at pin 1, which will be connected to the Arduino A0 pin. This circuit gets a voltage source from the power supply, then pin 3 or VCC on the GSR sensor is connected to 5V. Pin 4, or the ground on the GSR sensor is connected to the ground pin. Meanwhile in Figure 2(b), the heart rate sensor circuit gets a voltage of 5 volts from the power supply. This heart rate circuit will detect the heart rate using infrared as a light source, which will be emitted to the finger, and then the phototransistor will reflect and receive the light [18].



(a)



(b)

Figure 2. Hardware system (a) GSR sensor circuit and (b) Heart rate sensor circuit

2.3. Tool’s testing techniques

2.3.1. GSR parameter testing

The data testing for the GSR parameter is conducted by taking measurements from 5 respondents, with each respondent being measured 10 times. The results obtained from these measurements are then compared with the output values measured by a multimeter to assess the accuracy of the tool. The testing process is designed to identify any discrepancies between the tool's readings and the multimeter’s outputs, which could indicate potential calibration issues or sensor inaccuracies. This rigorous testing is essential for verifying that the GSR sensor accurately detects physiological changes related to stress, ensuring the overall reliability of the stress detection tool.

2.3.2. Heart rate parameter testing

The data testing for the heart rate parameter is performed by comparing the heart rate measurement results from the tool developed by the author with those from the finger pulse oximeter SONOSAT – F04T. This device can measure both oxygen levels and heart rate; however, in this case, only the heart rate readings in BPM are compared with the author’s tool. Data collection for this sensor testing is conducted on 5 respondents, with each respondent being measured 10 times. Data collection is carried out 10 times for each measurement.

2.3.3. Tool's result comparison with DASS 42

In this stage, the testing focuses on comparing the stress detection tool's results with the outcomes of the depression anxiety stress scales (DASS 42) test, which is a widely recognized psychological assessment tool. The purpose of this comparison is to evaluate the accuracy and reliability of the tool in determining the respondents' stress levels. The DASS 42 provides a benchmark by categorizing the respondents' emotional states into levels of depression, anxiety, and stress. By comparing the tool's output with the DASS 42 results, the study aims to validate whether the tool can accurately reflect the psychological conditions measured by the DASS 42. This comparison is crucial for ensuring that the tool is effective and can be used as a reliable method for stress detection in various settings.

3. RESULTS AND DISCUSSION

3.1. Fuzzy logic system

The fuzzy logic system is the central processing unit of this stress detection tool, responsible for interpreting the physiological data collected by the hardware sensors to determine the user's stress level. The fuzzy logic system processes the inputs from the heart rate and GSR sensors, converting these into membership functions that represent various states such as "very slow," "slow," "fast," and "very fast" for heart rate, and "very dry," "dry," "wet," and "very wet" for GSR. By applying a set of predefined rules, the system then infers the user's current stress level, categorizing it into one of four states: relax, calm, anxiety, or Stress. This method allows for a flexible and adaptable interpretation of the data, ensuring that the stress level output is tailored to the individual user's physiological responses.

3.1.1. GSR membership function

The GSR input in this tool is categorized into four types, each representing a different level of skin conductance as we can see in Figure 3. These categories range from very dry skin, indicating a relaxed state, to very wet skin, which is typically associated with higher stress levels. By dividing the GSR input into these four types, the tool can effectively gauge the intensity of stress experienced by the user, based on their physiological response as measured through skin conductance.

- Very Dry, GSR Value <2 Siemens
- Dry, GSR Value 2 - 4 Siemens
- Wet, GSR Value 3 - 5 Siemens
- Very wet, GSR Value >4 Siemens

Each membership function is defined by specific ranges of GSR values, with overlapping boundaries to allow for a smooth transition between categories. For instance, a GSR value below 2 Siemens might be classified as "Very Dry," indicating a low level of skin conductance typically associated with a relaxed state. As the GSR value increases, it might enter the "Dry" range (2 to 4 Siemens), suggesting a slightly elevated stress level. Higher GSR values, such as those between 3 and 5 Siemens, fall into the "Wet" category, indicative of a moderate stress level. Finally, GSR values exceeding 4 Siemens are classified as "Very Wet," signifying a high level of physiological arousal and likely stress.

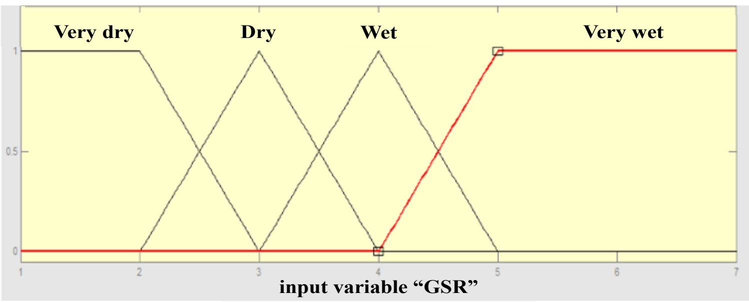


Figure 3. GSR input

3.1.2. Heart rate membership function

The heart rate input in this tool is classified into four types, each corresponding to a different range of BPM. These classifications are designed to reflect varying levels of physiological arousal, from very slow heart rates associated with a relaxed state to very fast heart rates indicating high stress or anxiety. By dividing

the heart rate input into these four types, the tool can accurately assess and respond to different levels of stress based on an individual's heart rate patterns.
- Very slow, heart rate 60-80 bpm
- Slow, heart rate 70-90 bpm
- Fast, heart rate 80-100 bpm
- Very fast, heart rate > 100 bpm

It can be seen in Figure 4 that the fuzzy input used to determine the body's heartbeat points in humans uses triangular and trapezoidal curves. These four curves are used as heart rate variables: very slow, slow, fast, and very fast heart rate. Each of these membership functions represents a specific range of BPM, which correlates with different physiological and emotional states of the user.

The "Very Slow" membership function typically covers heart rates in the range of 60 to 80 BPM, which are generally associated with a relaxed or resting state. This category is crucial for identifying when a user is in a calm and unstressed condition, as lower heart rates often indicate a lower level of arousal. As the heart rate increases, the fuzzy logic system transitions into the "Slow" category, which might encompass heart rates between 70 and 90 BPM. This range is often indicative of a slightly heightened state of alertness, but not necessarily stress. It could correspond to a state of calm attention, where the user is focused but not anxious.

Meanwhile, the "Fast" membership function, covering heart rates from 80 to 100 BPM, represents a moderate increase in physiological arousal. This range is significant because it can indicate the onset of stress or anxiety, where the body starts to respond to perceived challenges or threats with an elevated heart rate. Finally, the "Very Fast" membership function is applied to heart rates exceeding 100 BPM. This range is associated with high levels of stress or anxiety, where the user's cardiovascular system is highly activated. In this state, the heart is pumping rapidly, indicating that the user may be experiencing significant stress or emotional strain.

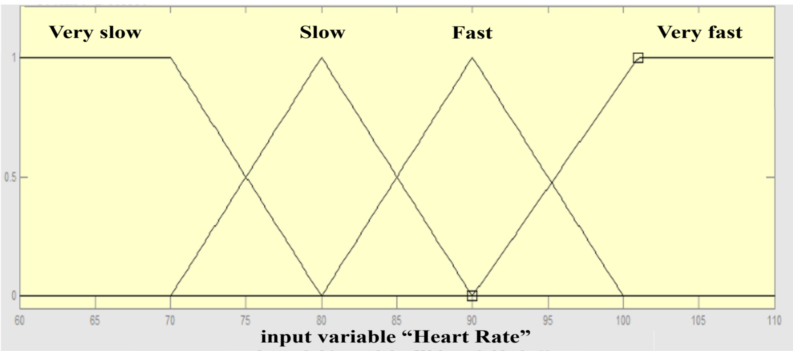


Figure 4. Heart rate input

3.1.3. Stress level (output) membership function

The output for determining the level of stress experienced by humans in this tool is categorized into four distinct types, each representing a different intensity of stress. These categories are designed to capture the full spectrum of stress responses, ranging from a completely relaxed state to severe stress. By dividing the output into these four types, the tool can provide a more precise and nuanced assessment of an individual's stress level, allowing for more targeted and effective stress management interventions.
- Relax (R) (0 – 25)
- Calm (C) (25 – 50)
- Anxiety (A) (50 – 75)
- Stress (S) (75 – 100)

It can be seen in Figure 5 that the fuzzy output is used to determine the decision results from the rules that have been made based on the heart rate and GSR values. There is a triangular shape curve for body condition variables in humans with four fuzzy: Relax (R), Calm (C), Anxiety (A), and Stress (S). Several rules are set in the stress level fuzzy system to get the desired output. From some of the input data, the following rule ensues. This decision will later serve as output. There are 2^4 (16) [19] rules that will produce the following outputs:
- If GSR is VERY DRY and heart rate is VERY SLOW, the RESULT is RELAXED.
- If GSR is DRY and heart rate is VERY SLOW, the RESULT is RELAXED.

- If GSR is WET and heart rate is VERY SLOW, the RESULT is CALM.
- If GSR is VERY WET and heart rate is VERY SLOW, the RESULT is CALM.
- If GSR is VERY DRY and heart rate is SLOW, the RESULT is RELAXED.
- If GSR is DRY and heart rate is SLOW, the RESULT is CALM.
- If GSR is WET and heart rate is SLOW, the RESULT is ANXIOUS.
- If the GSR is VERY WET and the heart rate is SLOW, the RESULT is ANXIOUS.
- If GSR is VERY DRY and heart rate is FAST, the RESULT is CALM.
- If GSR is DRY and heart rate is FAST, the RESULT is ANXIOUS.
- If GSR is WET and heart rate is FAST, the RESULT is ANXIOUS.
- If GSR is VERY WET and heart rate is FAST, the RESULT is STRESSED.
- If GSR is VERY DRY and heart rate is VERY FAST, the RESULT is CALM.
- If GSR is DRY and heart rate is VERY FAST, the RESULT is ANXIOUS.
- If GSR is WET and heart rate is VERY FAST, the RESULT is STRESSED.
- If GSR is VERY WET and heart rate is VERY FAST, the RESULT is STRESSED.

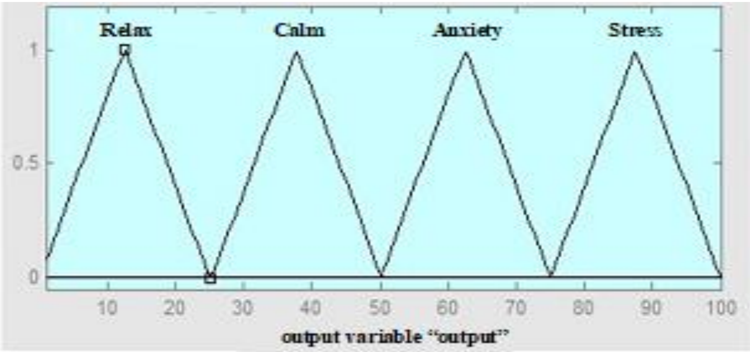


Figure 5. Stress level membership function

3.2. Tools performance test results

3.2.1. GSR test result

GSR parameter testing was carried out to determine the success of the work of the tool that the author made. This test is carried out by comparing the measurement results between the author's tools with the measured output using a multimeter. In this study, data collection was carried out 10 times on 7 respondents. The following are the results of the tests.

From Table 2, the GSR parameter test obtained the highest average of accuracy value of 99.78% for the respondent 6, and the lowest error percentage value of 97.47% for respondent 7. These results highlight the overall reliability and precision of the GSR sensor in detecting skin conductance changes, which are indicative of stress levels. The high accuracy values across the respondents demonstrate that the sensor consistently provides readings that are close to the actual measurements obtained through a multimeter, validating the effectiveness of the hardware design. The slight variations in accuracy among different respondents could be attributed to several factors, such as individual differences in skin properties, the positioning of the GSR sensor, or variations in ambient conditions during testing. For instance, factors like skin dryness, temperature, or slight movements during measurement might have influenced the GSR readings, leading to minor discrepancies. However, even in the case of respondent 7, where the accuracy was slightly lower at 97.47%, the error margin remained minimal, ensuring that the overall performance of the tool remains within acceptable limits for practical applications.

Table 2. GSR test result

No.	GSR Tests	Stress detection tool (average from 10 tests)	Multimeter (average from 10 tests)	Accuracy
1	Respondent 1	0.991	0.993	99.79%
2	Respondent 2	1.847	1.853	99.68%
3	Respondent 3	0.371	0.379	97.89%
4	Respondent 4	0.193	0.195	98.97%
5	Respondent 5	2.041	2.047	99.71%
6	Respondent 6	1.35	1.353	99.78%
7	Respondent 7	0.193	0.198	97.47%

3.2.2. Heart rate test result

A heart rate parameter test was carried out to find out the tool's performance. This test was carried out by comparing the measurement results between a pulse oximeter [20] and a tool made by the author. In this study, data collection was carried out 10 times on 6 respondents. The following is the result of testing performed on the tool.

From Table 3, the highest accuracy value is 99.63%, and the lowest accuracy value is 96.96%. These results highlight the heart rate sensor's ability to provide highly accurate measurements of BPM across different respondents. The high accuracy values indicate that the sensor's readings are closely aligned with those obtained from the pulse oximeter, validating the effectiveness of the hardware design. The consistently high performance of the sensor across multiple tests demonstrates its reliability in monitoring heart rate as an indicator of stress. The slight variation in accuracy, with the lowest value being 96.96%, still reflects a minimal error margin. This minor discrepancy suggests that while there may be small differences in individual readings, the overall accuracy remains within an acceptable range for practical use. The tool's ability to maintain such high accuracy across different respondents reinforces its suitability for reliable stress detection in real-world applications. These results confirm that the heart rate sensor is a robust component of the stress detection system, capable of delivering precise and dependable data.

Table 3. Heart rate test result

No.	Heart rate (BPM) tests	Stress detection tool (average from 10 tests)	Pulse oximeter (average from 10 tests)	Accuracy
1	Respondent 1	77.4	78.1	99.1%
2	Respondent 2	75	76.7	97.79%
3	Respondent 3	82.8	85.4	96.96%
4	Respondent 4	79.8	80.1	99.63%
5	Respondent 5	84.6	85.6	98.83%
6	Respondent 6	116.9	118	99.07%

3.3. Stress level testing based on GSR and heart rate using fuzzy logic.

In this test, GSR and heart rate (BPM) parameters were measured to find the stress level obtained by using the fuzzy logic method as a decision maker. Data were taken from 5 respondents with measurements 10 times for every respondent. Then the measurement results were compared with the results of the Depression Anxiety Stress Scales (DASS) 42 test [21].

3.3.1. Stress level test

The following data in Table 4 in Appendix were obtained based on the data collection results from 5 respondents who had done 10 trials in Table 3. From the results of data collection that was carried out using a stress detection tool, the first respondent stress level obtained by using the fuzzy logic method as a decision maker on a tool is having a relaxed (R) state. As well, the second respondent stress level condition was 100% relaxed (R). Meanwhile, third respondent had three conditions (from 10 tests): 20% relaxed (R), 70% calm (C), and 10% anxiety (A). Then, the fourth respondent stress level obtained by using the fuzzy logic method (10-time tests) is having a calm (C) condition 60% and anxiety (A) condition 40%. In contrast, of the 10 experiments conducted on the fifth respondent, he had relaxed (R) 100% conditions.

3.3.2. Depression anxiety stress scales (DASS 42) test

Depression Anxiety Stress Scale 42 (DASS 42) is a questionnaire consisting of 42 questions, each question has a score of 0-4 [22], [23]. In the DASS 42 test there are 3 scales made to assess the negative emotional level of depression, anxiety, and stress [24]. The DASS 42 scale can be classified into [25], [26]:

- The depression scale is found in questions number 3, 5, 10, 13, 16, 17, 21, 24, 26, 31, 34, 37, 38, 42.
- The anxiety scale is found in questions number 2, 4, 7, 9, 15, 19, 20, 23, 25, 28, 30, 36, 40, 41.
- The stress scale is found in questions number 1, 6, 8, 11, 12, 14, 18, 22, 27, 29, 32, 33, 35, 39.

Measurement of stress levels in a person can be grouped into 4 parts, namely, normal, moderate, severe, and very severe [27]. After filling in the questionnaire, the scores are added up and the categorization can be seen in Table 5 [28], [29].

Table 5. Categorization of stress level (DASS42)

Level	Depression	Anxiety	Stress
Normal	0 – 9	0 – 7	0 – 14
Mild	10 – 13	8 – 9	15 – 18
Moderate	14 – 20	10 – 14	19 – 25
Severe	21 – 27	15 – 19	26 – 33
Very Severe	>28	>20	>34

The following is Table 6, which presents the detailed results of the DASS 42 test administered to the respondents. This table captures the scores for depression, anxiety, and stress for each individual, providing a comprehensive view of their psychological state. By analyzing these scores, we can assess the severity of each emotional condition and compare these findings with the tool's stress level classifications to evaluate its accuracy and effectiveness.

From Table 6, five respondents answered 42 questions according to what each individual experienced in dealing with situations in their life. Based on the assessment from the DASS 42, the first respondent experienced mild depression (10 points), mild anxiety (8 points), and moderate stress (22 points). The second respondent experienced normal depression (8 points), mild anxiety (9 points), and normal stress (5 points), etc. These results provide a detailed profile of each respondent's emotional and stress levels, categorized into specific ranges that reflect their psychological state.

The DASS 42 test results reveal a range of emotional conditions among the respondents, from normal levels of depression, anxiety, and stress to more severe conditions. For instance, the first respondent's scores indicate that they are experiencing a moderate level of stress, which is significant enough to be noted, but not extreme. Meanwhile, the second respondent's scores fall within the normal range for both depression and stress, with only mild anxiety present, suggesting a relatively stable emotional state. The varying levels of emotional states across respondents illustrate the diversity in how individuals experience and report their psychological conditions.

Table 6. DASS 42 test on respondents

Respondent	Depression	Anxiety	Stress	Result (condition)
Respondent 1	10	8	22	Mild depression, Mild anxiety, Moderate stress
Respondent 2	8	9	5	Normal depression, Mild anxiety, Normal stress
Respondent 3	11	9	9	Mild depression, Mild anxiety, Normal stress
Respondent 4	7	21	13	Normal depression, Very severe, Normal stress
Respondent 5	6	6	10	Normal depression, Normal anxiety, Normal stress

3.3.3. Comparison of tools test and DASS 42

A comparison of tool testing and the DASS 42 test was carried out to compare the results of tools made with the DASS test to get accurate results, so the stress detection tool must be tested and compared with the DASS 42 test for measuring psychological stress [30], [31]. The comparison involved analyzing how well the tool's stress level classifications aligned with the results from the DASS 42, a widely recognized psychological assessment. This step was crucial in validating the accuracy and reliability of the stress detection tool, as the DASS 42 provides a standardized measure of depression, anxiety, and stress levels.

It can be seen from Table 7 that DASS has three conditions of depression, anxiety, and stress. Of the three emotional conditions there are several levels, namely normal/mild, moderate, severe, and very severe [32], [33]. Meanwhile, these psychological states are mapped to the stress levels detected by the tool: relax, calm, anxiety, and Stress. If of the three DASS conditions there are two or more levels that are the same as the tool, then the most dominating suitability level value can be taken [34]. For instance, a respondent who scores as "Mild" or "Normal" on the DASS 42 for depression and anxiety is generally categorized as "Relax" by the tool, while higher levels of stress or anxiety on the DASS 42 are translated into "Calm," "Anxiety," or "Stress" by the tool. This conversion is essential to compare the tool's performance directly with the established psychological test. The following are the results of a comparison of the test tool and the DASS 42 test in Table 8.

From the results in Table 8 that was carried out using a stress detection tool that was made and compared with the DASS 42 test, the first respondent had the result, namely relaxed (R) 100% (tool test result) and from DASS test 42 the results obtained were mild depression and mild anxiety, so from two mild conditions it can be converted into relaxed (R), so that the tool suitability level is 100%. Furthermore, the second respondent had the test tool result, which is 100% relaxed (R) and from the DASS 42 test the results obtained are normal depression and normal stress, so from two normal conditions it can be converted into relaxed (R), so that the level of suitability of the tool is 100%. While the third respondent had the tool test result that was 20% relaxed (R), 70% calm (C) and 10% anxious (A), from the DASS 42 test the results obtained were mild depression and mild anxiety. From those two mild conditions, it could be converted to relaxed (R), so that the tool suitability level was 20%. Then the fourth respondent had the tool test result that was 60% calm (C) and 40% anxious (A), while from the DASS 42 test the results obtained were normal depression and normal stress, so from two normal conditions it can be converted to relaxed (R) so that the level of conformity with the tool is 0%. The fifth respondent had the result which was 100% relaxed (R) and from the DASS 42 test the results obtained were normal depression, normal anxiety, and normal stress, so from three normal conditions it can be converted into relaxed (R). So that the level of suitability of the tool is 100%.

It can be concluded from the comparison of the data of 5 respondents who have done 10 trials of the stress detection tool with the DASS 42 test in Table 6 had an average suitability of 64%. The difference between the tool and the DASS 42 test could occur because during testing the tool might not have been installed correctly or when filling out the DASS 42 test questionnaire it did not match the condition of the respondent at that time.

Table 7. Conversion of DASS 42 result test to tool

No	Emotion State (depression, anxiety, and stress)	
	DASS 42	Tool
1	Mild, normal	Relax
2	Moderate	Calm
3	Severe	Anxiety
4	Very severe	Stress

Table 8. Comparison of tool with the DASS 42 test on respondent

Respondent	Tool Diagnostic Results	DASS 42 Test Results	Conformity Level
Respondent 1	Relax = 100%	Mild depression Mild anxiety Moderate stress	100%
Respondent 2	Relax = 100%	Normal depression Mild anxiety Normal stress	100%
Respondent 3	Relax = 20% Calm = 70% Anxious = 10%	Mild depression Mild anxiety Normal stress	20%
Respondent 4	Calm = 60% Anxious = 40%	Normal depression Very high anxiety Normal stress	0%
Respondent 5	Relax = 100%	Normal depression Normal anxiety Normal stress	100%
Tool conformity average			64%

3.4. Discussion

The stress detection tool developed in this study, which utilizes fuzzy logic to analyze GSR and heart rate data, demonstrated strong overall performance in classifying stress levels across a diverse set of individuals. The GSR parameter, in particular, showed high accuracy, with an average accuracy rate of 99.78%. However, the slight variations observed between respondents can be attributed to individual differences in skin properties and environmental factors. This indicates that the GSR sensor is highly reliable in detecting skin conductance changes that correlate with stress levels. Similarly, the heart rate parameter also performed well, with accuracy values ranging from 96.96% to 99.63%. The slightly lower accuracy in some instances indicates that further refinement in sensor calibration could enhance precision, especially in detecting subtle changes in heart rate associated with mild stress or anxiety. These findings suggest that both physiological measures are robust indicators of stress.

Moreover, fuzzy logic played a critical role in the effectiveness of this tool. By allowing for the categorization of stress levels into "Relax," "Calm," "Anxiety," and "Stress," fuzzy logic enabled the tool to handle the continuous and overlapping nature of physiological data, which traditional binary systems might struggle to interpret accurately. This approach allowed for a more nuanced classification of stress levels, particularly in cases where the physiological responses did not fit neatly into predefined categories. The tool's strong performance in these areas confirms the initial hypothesis that a fuzzy logic-based system would be effective for stress detection. However, the study also revealed that the tool's sensitivity to mild stress and anxiety could be improved, indicating the need for further refinement of the fuzzy logic algorithms.

The tool's overall conformity with the DASS 42 test results, which averaged 64%, indicates that while the tool is capable of correctly identifying stress levels in some cases, there are significant limitations in its current form. Although the tool showed high accuracy in detecting clear-cut cases of relaxation or high stress, it struggled to accurately classify more subtle or complex emotional states, such as mild stress or mixed anxiety and depression. This lower conformity rate suggests that the tool's fuzzy logic algorithms may need refinement to improve its sensitivity and specificity.

In comparison to related research [5], [6], which often relies on single-parameter tools for stress detection, this study's dual-parameter approach offers a more comprehensive method. However, the tool's performance, with an average conformity of 64%, suggests that while it is a step forward, it is not yet fully reliable. This finding points to the necessity of further research to enhance the tool's accuracy, particularly in detecting mild stress and anxiety, where it currently shows weaknesses.

4. CONCLUSION

Based on the data, the authors conclude that A stress detector designed using fuzzy logic as a decision maker method can work to detect stress with GSR and heart rate parameters with levels: relax, calm, anxiety, and stress. Experiments were also carried out by comparing the performance of the tool with the DASS 42 test, an accuracy of 64% was obtained. This could be caused because when the test was carried out the initialization of the tool was not ready and the condition of the respondent when carrying out the DASS test was different from when using the tool. Henceforth, validation of the performance of the tool will be carried out by involving a psychiatrist or psychologist.

APPENDIX

Table 4. Stress level test result on respondents

Respondent	Tests			Value
Respondent 1	1	G = 1.18 B = 84	R	R=10
	2	G = 1.17 B = 72	R	
	3	G = 1.18 B = 78	R	
	4	G = 0.97 B = 72	R	
	5	G = 1.17 B = 84	R	
	6	G = 1.09 B = 78	R	
	7	G = 0.97 B = 72	R	
	8	G = 1.18 B = 84	R	
	9	G = 1.07 B = 78	R	
	10	G = 1.17 B = 72	R	
Respondent 2	1	G = 0.62 B = 72	R	R=10
	2	G = 0.58 B = 72	R	
	3	G = 0.6 B = 78	R	
	4	G = 0.68 B = 78	R	
	5	G = 0.6 B = 72	R	
	6	G = 0.58 B = 78	R	
	7	G = 0.57 B = 72	R	
	8	G = 0.6 B = 78	R	

Table 4. Stress level test result on respondents *(continue…)*

Respondent	Tests	Value	Respondent	Tests
	8	G = 0.6	R	
		B = 78		
	9	G = 0.58	R	
		B = 78		
Respondent 3	1	G = 3.52	A	R = 2
		B = 90		C = 7
	2	G = 2.78	C	A = 1
		B = 84		
	3	G = 2.96	R	
		B = 78		
	4	G = 2.92	C	
		B = 84		
	5	G = 2.78	C	
		B = 84		
	6	G = 3.08	C	
		B = 84		
	7	G = 3.26	C	
		B = 78		
	8	G = 2.32	C	
		B = 84		
	9	G = 3.52	C	
		B = 84		
	10	G = 2.96	R	
		B = 78		
Respondent 4	1	G = 5.23	A	C = 6
		B = 84		A = 4
	2	G = 5.92	C	
		B = 78		
	3	G = 6.13	C	
		B = 78		
	4	G = 5.29	A	
		B = 84		
	5	G = 5.12	C	
		B = 78		
	6	G = 5.60	C	
		B = 72		
	7	G = 5.23	A	
		B = 84		
	8	G = 5.92	C	
		B = 78		
	9	G = 5.92	C	
		B = 78		
	10	G = 6.82	A	
		B = 84		
Respondent 5	1	G = 0.53	R	R=10
		B = 90		
	2	G = 0.55	R	
		B = 84		
	3	G = 0.52	R	
		B = 90		
	4	G = 0.57	R	
		B = 84		
	5	G = 0.53	R	
		B = 78		
	6	G = 0.52	R	
		B = 72		
	7	G = 0.58	R	
		B = 84		
	8	G = 0.56	R	
		B = 84		
	9	G = 0.52	R	
		B = 90		
	10	G = 0.53	R	
		B = 90		

Description:
G = GSR S = Stressed
B = BPM. R = Relax
C = Calm A = Anxiety

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