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Portable Stress Detection System for Autistic Children Using Fuzzy Logic

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ABSTRACT

Stress is prone to occur in children with autism. According to the study, around 85% of children who have autism suffer from anxiety disorders that can exacerbate their condition, leading to self-harm and harm to those in their vicinity. Heart rate, skin conductance, and finger temperature changes occur during stress. In this paper, we design a system to monitor heart rate, body temperature, and skin conductance to detect signs of stress. Subsequently, the measurement data is processed using the fuzzy logic (FL) method as a decision-maker algorithm. In particular, we use 64 fuzzy rules with membership functions for each parameter. Parameter measurement results will be displayed using a widget called Gauge, while stress conditions will be displayed using a label widget. The results will be displayed on the Blynk application with an IoT system and viewed remotely via Android devices. The test was conducted on five children aged 5-9 years with varying body conditions. From the test results, the mean accuracy of the heart rate sensor was 95.01%, the mean temperature sensor accuracy was 97.7%, and the mean conductance sensor accuracy was 93.75%. The stress levels range from a minimum of 25% to a maximum of 75%. These findings indicate that the developed tool has performed effectively, and it is feasible to monitor its operation remotely.

INTRODUCTION

Stress is prone to occur in childhood and adolescence. Children and teenagers who face challenging circumstances in their lives, such as the loss of a parent, divorce within their family, and instances of bullying, are likely to encounter difficulties with their mental well-being [1]. Stress experienced by a person can affect his/her psychological and physical health [2]. For example, it can affect growth, metabolism, reproduction, and immunity [3]. In addition, stress can also affect a person's behavior [4]. People with autism, especially children, may also experience stress in their lives [5]. People with autism are characterized by a lack of interaction or communication verbally and non-verbally, as well as making repetitive movements [6]. According to a study, there is a higher incidence of autism among males compared to females [7].

Approximately 85% of children with autism also have anxiety disorders, which can worsen their condition [8]. Stressors for children with autism may include sudden changes in their environment or sensory discomfort, sometimes leading to self-injurious behavior [9]. Recognizing these triggers and providing appropriate assistance and interventions is crucial for their well-being. Stress induces physiological changes in the body, affecting heart rate, fingertip temperature, and skin conductance [10]. Children with autism often exhibit different physiological responses compared to typical children, with higher heart rates and body temperatures and lower skin conductance levels [11].
A system to detect stressful conditions in children with autism should be designed to make it easier to detect existing stress conditions. Authors in [12] produced a tool capable of detecting stress using temperature and heart rate sensors in humans. However, an Internet of Things (IoT) platform is required to make the resulting system work more effectively. Authors in [13] designed a device capable of detecting stress using IoT-based heart rate and skin conductance sensors. However, only two types of sensors were utilized.

According to the American Psychological Association, stress comes in three types: acute, episodic acute, and chronic [16]. It can lead to various health issues, including hypertension and headaches [13]. Stress during pregnancy may impact fetal brain development and increase autism risk [17]. Children with autism can experience seizures and self-harming tendencies due to heightened anxiety [18]. Stress triggers physiological changes like altered heart rate, body temperature, and skin conductance [8], [11], [18]. Tables 1 and 2 show differences between typical children and those with autism. Typical children have a heart rate of 60-100 BPM, body temperature of 36-37ºC, and skin conductance of 2-4 µS, while children with autism often exhibit a heart rate of 70-110 BPM, body temperature of 37-38ºC, and skin conductance of 1-3 µS.

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Table 1. Changes Parameters in Normal Children

Condition	Heart Rate (BPM)	Body temperature (ºC)	Skin Conductance (μS)
Normal	60-100	36-37	2-4
Stress	100-120	32-36	4-6

Table 2. Changes Parameters in Children With Autism

Condition	Heart Rate (BPM)	Body temperature (ºC)	Skin Conductance (μS)
Normal	70-110	37-38	1-3
Stress	110-130	33-37	3-5

In [19], the Shimmer3 GSR+ sensor was employed to detect stress, analyzing signals like heart rate and blood pressure. A fuzzy logic approach determined stress levels. In [8], a 2R shimmer sensor assessed stress through heartbeat signals from various movements. Researchers in [17] utilized pulse sensors and GSR to measure heartbeat and skin conductance, using fuzzy logic to gauge stress. In [11], an E4 Wristband identified stress via electrodermal activity, employing fuzzy logic for stress level determination. In contrast, the Likert Scale and physiological and GSR data were employed to assess stress levels. In [21] utilized BioHarness™3, Shimmer Sensor, and MindWave Mobile EEG to monitor heart rate, electrodermal activity, and brain electrical signals. The Kolmogorov-Smirnov method assessed stress by employing Si7021 and a 3-axis Accelerometer to measure temperature, humidity, and movement, using fuzzy logic for stress assessment.

In this paper, we design an IoT-based portable stress detection device that addresses the gaps from previous research works. This research work will be focused on children with autism by combining the results of research that has been done previously. The design includes several sensors, including the DS18B20 sensor for body temperature, the MAX30100 sensor for heart rate, and the GSR sensor for skin conductance. Furthermore, we use a fuzzy logic algorithm to improve decision-making and strive for higher accuracy than instruments used in previous studies. Moreover, fuzzy logic algorithms can analyze insufficient data effectively [14] and realize existing real information and do it with a simple approach [15]. In addition, this study will also use the ESP-32 Wi-Fi module so that the results of sensor measurements and stress conditions can be displayed on an Android device. The IoT system is used to make it easier to send data via the internet to devices such as laptops or Android and can be done in real-time and remotely to save time in managing and displaying data.

This paper presents a significant contribution to the field of autism research stress detection device specifically designed for children with autism. This innovative device can simultaneously measure several physical parameters, including heart rate, body temperature, and skin conductance. Its potential impact is substantial, as it can serve as a crucial tool for identifying signs of stress in children with autism, enabling timely intervention. The device's decision-making algorithm, based on fuzzy logic, ensures accurate stress level identification. Furthermore, the system is integrated with IoT technology, allowing for real-time and remote access to measurement results via Android devices. The research is supported by the use of three sensors—DS18B20, MAX30100, and GSR—which collectively provide valuable information for stress monitoring and intervention.

METHODS

The method in this study consists of four parts, i.e., hardware setup, software setup, measuring system, and data collection, as shown in Figure. 1.

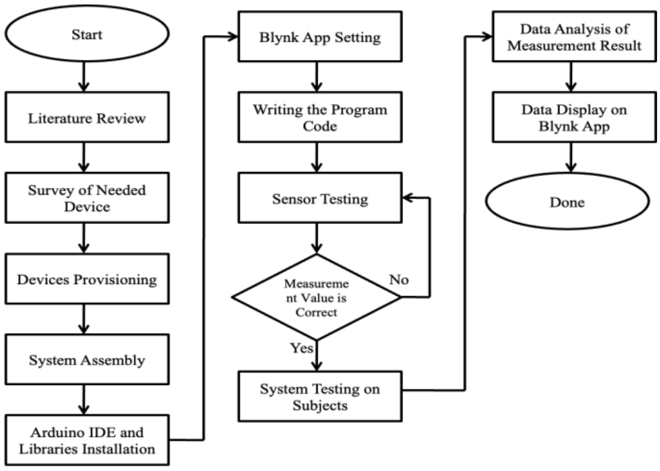


Figure 1. Method proposed

Hardware setup

This study utilizes three sensor types: the MAX30100 temperature sensor, the MAX30100 heart rate sensor, and the GSR skin conductance sensor. The GSR sensor detects emotional changes through sweat glands and operates at 3.3 V [23]. The MAX30100 sensor provides real-time measurements with high accuracy, featuring 2 LEDs, low noise, and a voltage range of 1.8-5 V [24]. The DS18B20 sensor offers advantages like a 1-wire interface, 64-bit ROM data storage, independence from external components, and compatibility with a voltage range of 3-5.5 V [25]. These sensors are connected to the ESP-32 device, serving as a microcontroller and Wi-Fi module. The setup includes three 4.7 KΩ pull-up resistors connected to the MAX30100 sensor's SCL and SDA pins and the DS18B20 sensor's Data pin, as shown in Figure 2.

Software setup

This study uses Arduino IDE software to write system programs. Before writing the program, a set of software, namely the MAX30100 sensor library, DS18B20, ESP-32, fuzzy logic, and the Blynk application, is needed. The fuzzy logic algorithm is assigned a membership function for each sensor, namely “very slow”, “slow”, “fast”, and “very fast” for heartbeat; “very hot”, “hot”, “cold”, and “very cold” for body temperature; and “very low”, “low”, “high”, and “very high” for skin conductance; and “normal” and “stress” membership functions for system outputs.

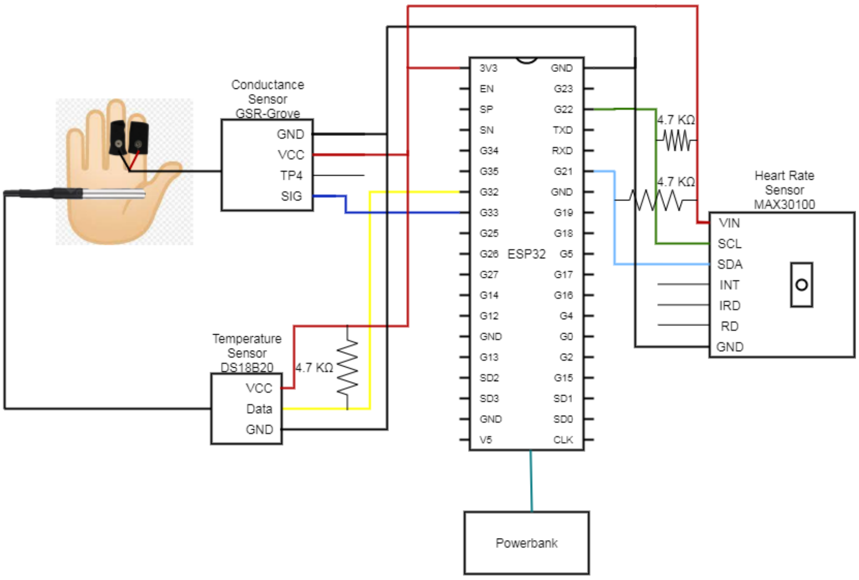


Figure 2. Diagram Block System

The blynk application includes the datastream and widgets settings. Five datastreams will be used, namely for heart rate, body temperature, skin conductance, stress percentage, and stress conditions, each of which has a Widget to display the results, namely "Gauge" for heart rate, body temperature, skin conductance, and stress percentage, and "Label" for stress conditions. The appearance of existing stress conditions will also be differentiated based on the color of the writing, namely "blue" for normal conditions and "red" for stress conditions.

Data Collection

This study assessed a sample of five children with autism at the My Hope Special Needs Center Foundation in Banda Aceh. The sample consisted of three boys and two girls, ranging in age from 5 to 9 years. Parameters of body temperature, heart rate, and skin conductance were measured. The body temperature parameter was measured using the DS18B20 sensor, a handheld device. The heart rate parameter was measured using the MAX30100 sensor, which was used by placing the tip of the thumb or forefinger on the sensor. Skin conductance parameter was measured using the GSR sensor placed on the index and middle fingers. Measurements were carried out in 20 repetitions for 15-30 minutes.

Before being used on children with autism, the accuracy and precision values of the three sensors were tested. The accuracy value of the DS18B20 sensor was compared with a dotory-type thermometer, the accuracy value of the MAX30100 sensor was compared with an Omron-type tensimeter, and the accuracy value of the GSR sensor was compared with a digital multimeter by changing the multimeter output from Ω units to μS using the formula [20]:

$$Skin\ Conductance = \frac{1}{Skin\ Resistance} \tag{1}$$

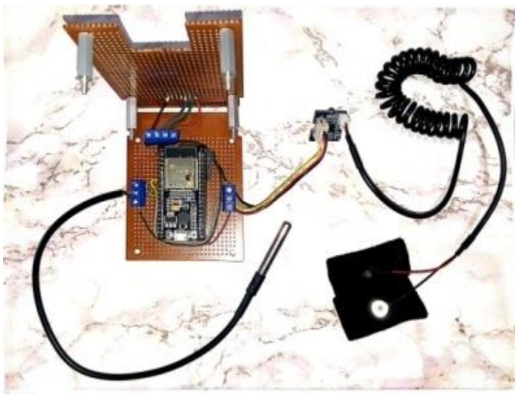
The accuracy can be represented using the error percentage as follows.

$$Error\ Percentage = \frac{|Test\ Result - Measure\ Result|}{Test\ Result} \text{x } 100 \tag{2}$$

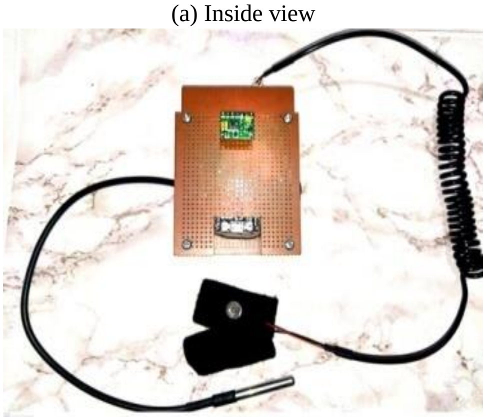
RESULTS AND DISCUSSION

Design System Result

In this section, the results of the series of tools that have been made will be displayed which measure 9 x 7 cm and consist of the MAX30100 sensor, DS18B20 sensor, GSR sensor, and ESP-32. Figure 3 shows the results of the tools that have been assembled.



(a) Inside view



(b) Outside view

Figure 3. The Measurement Device

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Based on Figure 3(a), it can be seen that the tool is assembled in such a way on a small PCB board by connecting the three sensors on the ESP-32 as a microcontroller that will control the performance of the tool so that in Figure 3(b) it can be seen that only the three sensors are on the outside so that it facilitates the use and transfer of the device.

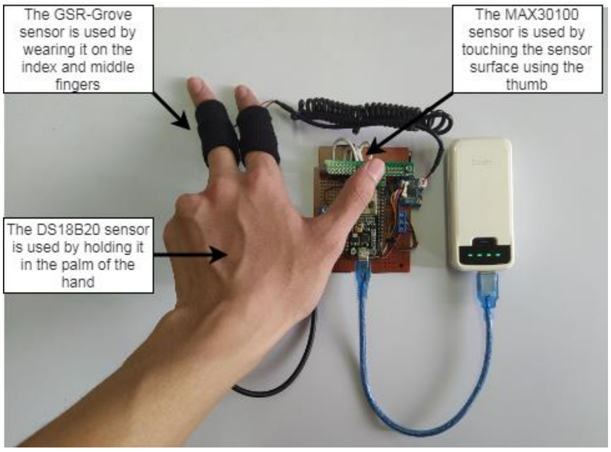


Figure 4. Equipment Used

Figure 4 demonstrates the functioning of the device once it is connected to a power source, where we used a power bank in the experiment. The placement of the three sensors is crucial, with the MAX30100 sensor positioned on the tip of the thumb or index finger, the DS18B20 sensor held by the user, and the GSR sensor placed on the index and middle fingers. Subsequently, the three sensors will collect parameter measurements, which will be processed by the ESP-32 utilizing the Fuzzy Logic method. The measurement outcomes and stress conditions will then be displayed on the blynk application.

Hardware Testing

MAX30100 Sensor Accuracy Testing

Heart rate was measured using the MAX30100 sensor, which emits red light onto the finger. Hemoglobin absorption of this light varies with blood oxygen levels. The photodetector captures unabsorbed light, converting it into an analog electrical signal, which is then amplified, filtered, and stored in a FIFO buffer. Sensor functionality was confirmed when LED lights remained on during testing and measurement data was obtained. The sensor's accuracy was assessed by comparing its one-minute average reading with an Omron-type tensiometer, yielding results in Table 3.

Table 3. The Results of Testing the Accuracy of the MAX30100 Sensor

Reading		Average (BPM)	Error (%)
Sphygmomanometer (BPM)	**MAX30100 (BPM)**		
95	103.54 104.17 102.72 98.52 91.04	99.998	4.99

Testing of DS18B29 sensor

The DS18B20 temperature sensor detects body temperature by converting skin heat into electrical energy. It measures temperature based on changes in resistance and electric current caused by temperature fluctuations. Sensor functionality was confirmed through successful data collection, and accuracy was evaluated by comparing its one-minute average reading to that of a dotory-type thermometer (see Table 4).

Table 4. The Results of Testing the Accuracy of the DS18B20 Sensor

Reading		Average (ºC)	Error (%)
Thermometer (ºC)	**DS18B20 (ºC)**		
36.5	35.69 35.63 35.69 35.69 35.69	35.678	2.30

Based on Table 4, it can be seen that the body temperature readings when using a thermometer and sensor are then found to have an error percentage of 2.30% using Eq. (2).

Testing of GSR sensor

Electrodes on the index and middle fingers can be used to power the GSR sensor, which detects skin conductance. Because sweat glands are strong conductors, an electric current will flow to both electrodes, and the current transmitted will be affected by the sweat glands generated by the skin. To acquire the skin conductance value, changes in the existing electric current will be magnified and caught by the sensor. If the measurement data can be read, the GSR sensor is operational. The GSR conductance sensor will be tested by comparing its average value for 1 minute with a digital multimeter. The multimeter readings will be translated into μS units using Eq. (1). The test results are shown in Table 5. Based on Table 5, it can be seen that the skin conductance readings when using a multimeter and sensor are then found to have an error percentage of 6.25% using Eq. (2).

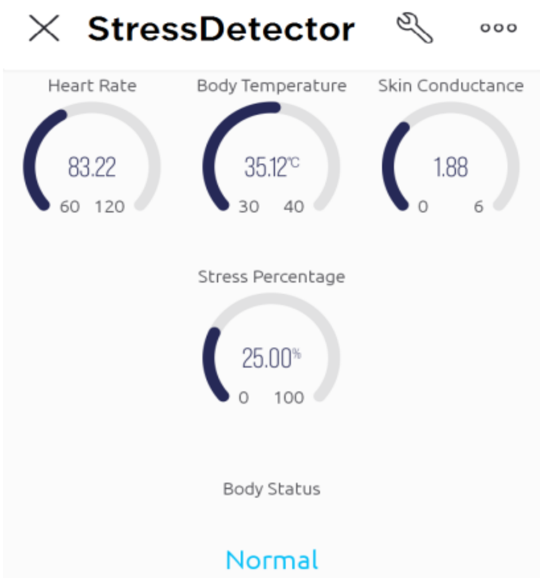
Table 5. The Results of Testing the Accuracy of the GSR Sensor

Reading			Average (μS)	Error (%)
Multimeter (Ω)	**Multimeter (μS)**	**GSR (μS)**		
560,000	1.785	1.89 1.89 1.93 1.92 1.89	1.904	6.25

Software testing

Testing on the Blynk application that has been set up. Testing aims to see whether the Datastream and Widgets that have been set up can function properly or not. Then the test can be shown as Figure 5 as follows.

Figure 5 shows that the Blynk application functions properly because the minimum-maximum value and unit of measurement are appropriate. The display on the gauge widget can change according to the results obtained. The label widget results also work well because they can display stress conditions and have



(a) First test

(b) Second test

Figure 5. Fuzzy Logic and Blynk Test Result

writing colors that follow what has been determined, namely blue for normal conditions and red for Stress conditions.

Based on Table 6, the fuzzy rule that has been determined has worked well, and the results obtained from the two trials. The label widget results also work well because they can display stress conditions and have writing colors under what has been determined, namely blue for normal conditions and red for stress conditions.

Analysis of stress detection results

In this section, we will use the tool on children with autism. As mentioned above, the device will be tested on five children of different genders and ages. This tool will measure the value of heart rate, body temperature, and skin conductance. The measurement values obtained will be processed based on the Fuzzy Rule that has been determined so that the measurement parameter values, stress percentage, and stress conditions experienced by children with autism will be obtained.

Based on Appendix 1, it can be seen that the test was conducted on 5 children 20 times with different periods. The test was conducted to get the percentage value of body parameters from heartbeat, body temperature, skin conductance, and body circumstances. The results show 5 children with body parameter conditions that vary between normal and stress. The lowest normal body circumstances value is 25%, and the highest is 46.89%. As for stress conditions, the lowest body circumstances value for stress conditions is 52.99%, and the highest is 75%. Based on the results obtained, it can be said that the portable stress detection device can work well because it can detect the state of body parameters of autistic children.

To develop a portable stress detection device for children with autism, this research analyzed several related studies. These studies used a variety of decision-making methods and different sensors/devices. The analysis results show that using the Fuzzy Logic method in the tool developed by this research provides a comprehensive approach to identifying stress levels. DS18B20, MAX30100, and GSR sensors are integrated into this device and connected with IoT technology for real-time monitoring. However, this research still has several limitations, including the number of trial participants being limited to five children with a relatively small age range (5-9 years) and dependence on internet stability. Nevertheless, this research has great potential to be a useful tool in identifying signs of stress in children with autism. A comparison between various studies related to this research, each with different models and techniques, can be seen in Table 7.

Table 6. Fuzzy Logic and Blynk App Test Results

Heartbeat	Body Temperature	Skin Conductance	Body Circumstances	*Fuzzy Rule*	Result
83.22 BPM (Slow)	35.12ºC (Cool)	1.88µS (Low)	Normal	Normal	Achieved
65.52 BPM (Very Slow)	32.62ºC (Very cool)	1.03µS (Very low)	Stress	Stress	Achieved

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Table 7. The Advantages and the Drawbacks of Our Work

Authors	Decision Making / Methods	Sensor/Device	Advantages	Drawbacks
Whiston, A. 2022 [26]	• Depression Anxiety and Stress Scale-21-S (DASS-21-S) • Beck's Depression Inventory-II (DBI-II)	• Wrist-band with sensor EDA	• Can be monitored on an ongoing basis • Valid and reliable method.	• Relies on individual subjective observations. • Reliance on the individual's honesty and understanding of symptoms.
Barki, H. 2023 [27]	• CNN	• Ear-mounted sensor photoplethysmography (PPG)	• More detailed signal analysis with CWT. • Obtain high accuracy up to 96.02%.	• Does not cover the entire spectrum of mentally stressful situations. • Generally CNN is used for image recognition.
Valenti, S. 2023 [28]	• Extraction of various physiological indices (heart rate) and its variability	• Ring-shaped probe with PPG and GSR sensors.	• PPG and GSR sensors integrated in one probe. • Can detect oxygen levels in the blood.	• Focuses only on data acquisition and physiological signal analysis • not real-time.
Shajari, S. 2023 [29]	• Enzim-Linked Immunosorbent Assay (ELISA)	• Microsweat with sensor Cortisol	• Can be used in a variety of environmental conditions	• Large production costs may be a limiting factor.
Talaat, F. M. 2023 [30]	• RF, XGBoost, DT, OSM	• Wrist-band with sensor GSR, PPG, and ACC	• effective stress monitoring with IoT and Machine Learning.	• Requires large data and has the potential for overfitting in Machine Learning models.
Proposed Method	• Fuzzy Logic	• Rings with sensor DS18B20, MAX30100, dan GSR	• Using Fuzzy Logic for stress decision making • System integration with IoT	• Dependence on the stability of the internet • The trial was only carried out on five children with a relatively small age range (5-9 years)

CONCLUSION

Based on the research that has been done, it can be concluded that the assembled device has functioned properly. This study shows the effective functionality of the developed IoT-based portable stress detection device for children with autism. The device integrates DS18B20 for body temperature, MAX30100 for heart rate, and GSR for skin conductance sensors. The device uses a fuzzy logic algorithm with 64 rules to accurately assess stress levels based on physiological parameters. Real-time data transmission via the ESP-32 Wi-Fi module and the Blynk application allows remote monitoring and intervention. The device demonstrates high accuracy in stress detection, 95.01% for heart rate sensors, 97.7% for body temperature sensors, and 93.75% for skin conductance sensors. The fuzzy logic method effectively determines stress conditions, evidenced by consistent outputs across two test phases, aligning with predefined fuzzy rules. These results are accessible remotely via an Android device's IoT system. Future research should expand the study's sample size and validate the device's performance across diverse populations. Additionally, enhancements in data analytics and integration with advanced algorithms could further refine stress detection capabilities.

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APPENDICES

1. Overal Test Result of the Device

No.	Age	Time-paused (Mins)	Heartbeat (BPM)	Body Temperature (ºC)	Skin Conductance (µS)	Body Circumstances	Fuzzy Rule
1	5	28	61.06	34.94	1.81	28	Normal
			78.63	32.62	1.87	75	Stress
			89.08	34.31	1.83	46.89	Normal
			114.9	31.94	1.83	75	Stress
			60.11	34.25	1.85	45.74	Normal
			108.74	34.62	1.83	69.37	Stress
			88.09	33.31	1.88	65.47	Stress
			98.6	35.69	1.86	48.91	Normal
			95.79	33.88	1.85	62.27	Stress
			76.25	35.5	1.87	25	Normal
			85.67	34.06	1.86	46.39	Normal
			65.64	33.56	1.85	57.79	Stress
			82.99	33.25	0.86	64.46	Stress
			81.96	34.5	0.67	42.15	Normal
			87.07	33.31	1.01	63.6	Stress
			76.18	33.62	1.79	56.56	Stress
			60.64	34.38	1.07	43.44	Normal
			70.89	35.44	1.11	25	Normal
			92.14	34.88	0.43	33.51	Normal
			61.84	34.38	0.74	43.44	Normal
2	9	16	91.58	35.5	1.57	34.16	Normal
			62.26	33.38	1.86	61.98	Stress
			86.31	35.88	1.15	25	Normal
			88.78	35.62	0.65	25	Normal
			61.74	33.25	0.89	65.39	Stress
			94.3	34.94	0.44	39.34	Normal
			68.45	35	0.72	25	Normal
			97.31	33.25	1.86	64.35	Stress
			82.84	33.44	1.17	59.56	Stress
			64.93	35.62	1.19	25	Normal
			73.22	33.56	1.1	57.79	Stress
			63.53	33.44	1.18	60.48	Stress
			71.75	35.38	1.19	25	Normal
			64.01	33.56	1.19	57.79	Stress
			62.71	35.94	1.18	25	Normal

No.	Age	Time-paused (Mins)	Heartbeat (BPM)	Body Temperature (ºC)	Skin Conductance (µS)	Body Circumstances	Fuzzy Rule
			63.25	35.5	1.14	25	Normal
			65.23	34.88	1.19	30.58	Normal
			76.57	32.75	1.15	75	Stress
			62.85	35.5	1.09	25	Normal
			95.99	35.5	1.12	42.93	Normal
3	8	28	63.56	32.88	1.82	75	Stress
			60.93	32.81	1.88	75	Stress
			63.01	32.62	1.85	75	Stress
			79.26	32.28	1.85	75	Stress
			62.51	33.25	1.83	65.28	Stress
			90.38	33.19	1.86	67.3	Stress
			102.37	34.06	1.86	62.73	Stress
			99.94	33	1.85	75	Stress
			70.98	35.62	1.83	25	Normal
			72.17	34.94	1.12	27.94	Normal
			78.5	35.75	1.85	25	Normal
			67.52	35.75	1.88	25	Normal
			64.81	34.19	0.57	46.84	Normal
			77.61	34.25	0.82	45.8	Normal
			110.88	33.81	0.88	75	Stress
			87.54	34.44	1.18	42.21	Normal
			75.24	34.75	0.59	35.05	Normal
			106.19	35.31	1.8	61.81	Stress
			65.28	33.62	1.01	56.56	Stress
			106.69	34.25	0.99	61.96	Stress
4	7	26	63.23	33.31	1.82	63.54	Stress
			116.57	32.12	1.87	75	Stress
			71.92	33.56	1.84	57.79	Stress
			88.18	34.25	1.86	46.56	Normal
			70.7	32.31	0.8	75	Stress
			63	33.38	1.88	61.98	Stress
			69.04	32.75	1.88	75	Stress
			66.99	32.94	1.88	75	Stress
			73.26	34.38	1.87	43.44	Normal
			69.19	34.94	1.89	27.93	Normal
			66.47	33.81	1.88	53.16	Stress
			67.71	34.38	1.86	43.44	Normal
			91.11	33.69	0.91	55.38	Stress
			94.94	32.56	1	75	Stress
			84.08	34.25	0.74	45.74	Normal
			94.76	32.69	0.94	75	Stress
			81.23	33.19	0.73	65.94	Stress
			79.92	32.75	0.59	75	Stress
			70.54	35.31	1.84	25	Normal
			79.8	35.62	1.84	25	Normal
5	7	26	71.94	32.94	1.86	75	Stress
			75.76	31.25	1.84	75	Stress
			74.06	31.81	1.86	75	Stress
			63.88	35.12	1.84	25	Normal
			70.94	33.75	0.99	54.26	Stress
			74.98	34.19	1.86	46.84	Normal
			104.62	35.5	1.87	58.98	Stress
			72.51	33.31	1.88	63.6	Stress
			68.47	34.38	1.87	43.44	Normal
			78.37	33.38	1.89	60.41	Stress
			96.88	35.5	1.86	48.67	Normal
			69	35.31	1.84	25	Normal
			60.18	34.38	0.92	43.44	Normal
			68.42	33.12	0.74	69.58	Stress
			61.99	34.19	0.74	46.84	Normal
			93.15	35.44	0.76	34.69	Normal
			71.97	34.12	0.9	47.91	Normal
			101.78	34.5	1.16	52.99	Stress
			68.54	32.69	1.05	75	Stress
			88.76	32.88	1.17	75	Stress

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