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Multisensory Health Monitoring Device Based on Raspberry Pi 4B

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ABSTRACT

The availability of health monitoring devices that can be used independently, conveniently, and portably is increasing in line with busy lifestyles and the difficulty of scheduling medical tests. Measuring vital body signals with various devices makes measurements longer, less effective, and relatively more expensive. The proposed research can monitor vital body signals, such as heart rate, body temperature, respiratory rate, oxygen saturation, GSR, blood pressure, and snoring, which are integrated into a Raspberry Pi 4B-based device, with results displayed on an LCD screen. Data acquisition results show reasonably good accuracy in almost all parameters but require improvement in respiratory rate measurements. In the subsequent work, these seven-acquisition data will be used to predict several possible diseases.

1. Introduction

The rapid technological advancements and economic progress today have brought about changes in human life. These changes have made it necessary for humans to constantly compete in their lives. This often results in people not having enough time for routine health tests. Routine medical tests can provide insights into one's current health status, allowing diseases to be detected and prevented earlier [1]. Meanwhile, medical tests heavily rely on medical practitioners who must serve a large number of patients with limited automated monitoring tools.

Therefore, the current circumstances have prompted the availability of health devices that can be used directly and easily but can assist individuals in monitoring their health in real-time without the need to always visit a doctor.

In line with emerging needs, modern technology, as a result of the digital era and scientific advancements, has had a positive impact on human life. Evolving modern technology in the field of healthcare plays a crucial role in helping to detect and prevent diseases as well as monitor patient health. Various vital signs of the body need to be monitored to determine an individual's health condition.

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There is a plethora of research that utilizes physiological signals of the body to assess human health. Gupta *et al.,* [2] measures respiratory rate to assess human health, while Caldeira *et al.,* [3] measures genital temperature in women to predict ovulation periods. Wu *et al.,* [4] utilizes neck vibrations to detect obstructive sleep apnea (OSA), whereas A.K. Jayanthy *et al.,* [5] analyse OSA using ECG signals. Research by Filipa *et al.,* [6] calculates heart rate variability (HRV) estimates through PPG signals to detect heart abnormalities. Additionally, studies by Anusha *et al.,* [7], Ali *et al.,* [8], and Gita *et al.,* [9] all detect electrodermal activity to identify various factors such as stress levels, hydration levels, and pain levels.

Conventional physical check-ups require various different devices, performed separately and take longer time. Therefore, researchers have been striving to create a single device capable of measuring multiple parameters using multiple sensors. The challenge they face is how to create a low-cost wearable device that is also highly reliable and multifunctional.

Several studies have utilized multi-sensors with various parameters to comprehensively evaluate human health. For example, Nosirov *et al.,* [10] measured air quality parameters using MQ135, heart rate, accelerometer, air pressure, sound detection, temperature, humidity, and patient location. This study focused more on measuring the environmental parameters around the patient to assess their impact on the patient. Yu *et al.,* [11] designed a smart armband capable of measuring temperature, pulse, and position parameters using a triaxial accelerometer. This armband is very lightweight, weighing only 42 grams. However, it only includes 2 sensors to measure physiological signals and is primarily focused on monitoring elderly people.

Seulki *et al.,* [12] designed a low-power consumption device to simultaneously measure electrocardiogram (ECG), bio-impedance (BioZ), photoplethysmography (PPG), galvanic skin response (GSR), and heart sounds. However, this research used two microcontrollers and was specifically designed to detect congestive heart failure. Budi *et al.,* [13] also detected coronary heart disease early using parameters such as cholesterol, blood pressure, and heart rate.

Meanwhile, Liu *et al.,* [14] used a chest-mounted belt system to place sensors measuring ECG, respiration, temperature, and patient movement for monitoring, especially for elderly people. However, in this study, data collected by all these sensors were directly stored on a mobile device, limiting storage capacity.

There are also multi-sensor research studies using commercially available boards, as seen in the research conducted by Norhayati Mohd *et al.,* [15]. This study utilized an e-Health Platform and parameters such as temperature, pulse oximeter, and air flow for continuous human health monitoring. However, the product is relatively expensive and has been discontinued.

Grochala *et al.,* each [1] monitored daily activities using multiple parameters, including ECG, respiration, body temperature, barometric pressure, light intensity, and accelerometer. Unfortunately, this research still relies on a personal computer as the data processor, making it non-portable. Our previous research, conducted by Madona *et al.,* [16,17] used five physiological signal parameters to assess human stress levels. The parameters employed included GSR, Pulse, respiration rate, blood pressure, and body temperature. Aamir *et al.,* [18] also classified human stress levels using electroencephalograph (EEG), GSR, and PPG parameters. All three studies primarily focused on using these parameters to detect stress levels.

Upon closer examination, several studies with different disease or condition detection focuses actually utilize some of the same parameters. Therefore, in this research, we propose a device for health monitoring with various sensors for different disease detections. Our signal acquisition system is built using seven sensors, and the variations in future research can be employed to detect various conditions such as arrhythmia, OSA, and human stress levels.

2. Materials and Methods

Figure 1 illustrates the block diagram of the proposed prototype. There are 7 parameters to be acquired, namely temperature, snoring, pulse, respiration, GSR (Galvanic Skin Response), oxygen saturation, and blood pressure.

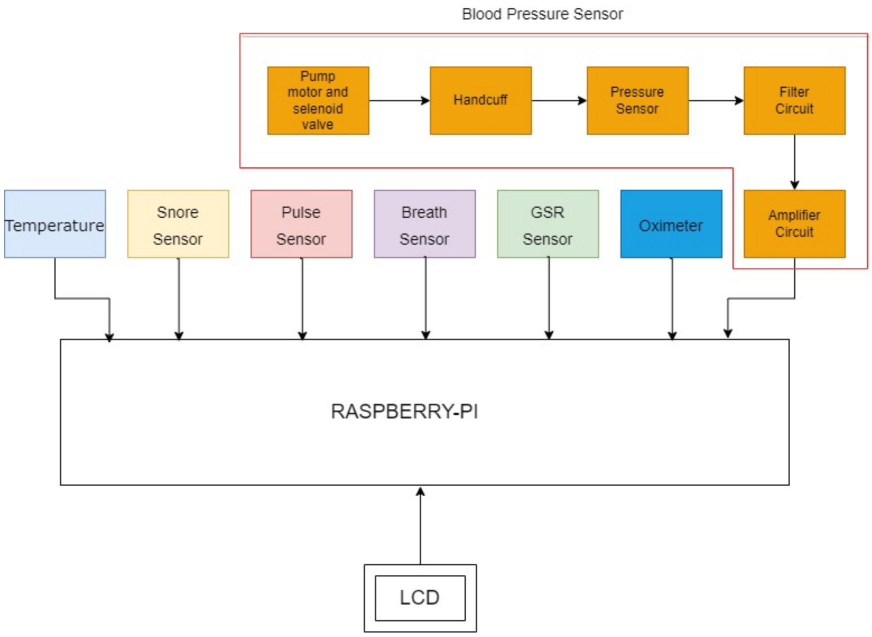

Fig. 1. Block Diagram of Multisensory Health Monitoring Device

The relationship between the components and the Raspberry Pi is depicted in the schematic diagram in Figure 2.

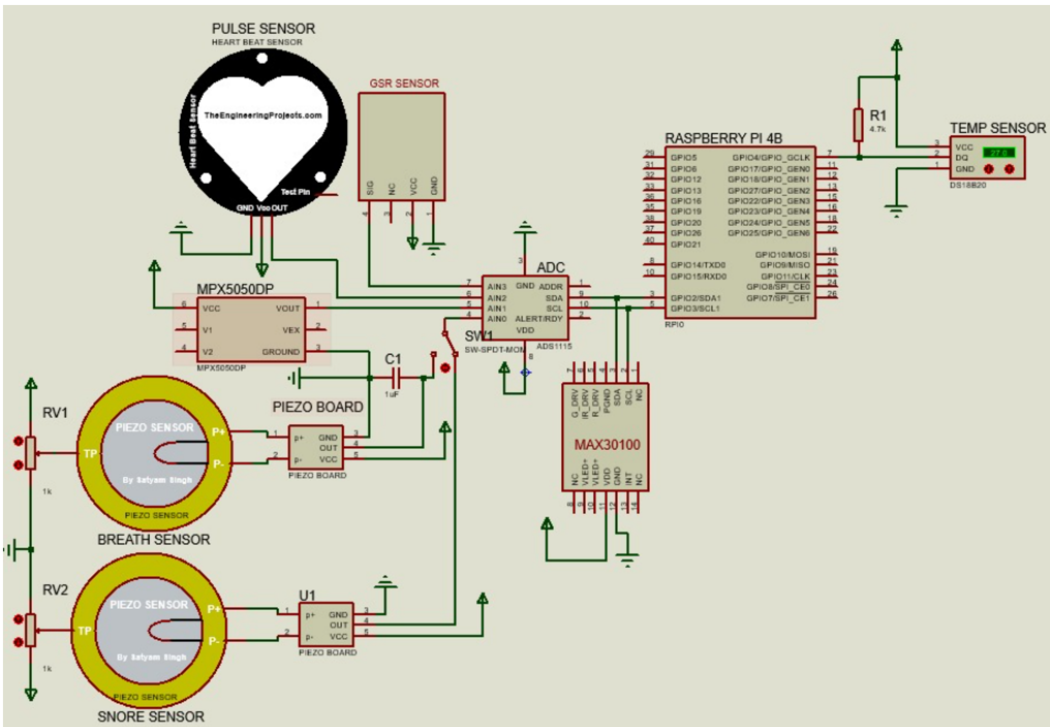

Fig. 2. Schematic Circuit of the Multisensory Health Monitoring Device

2.1 Body Temperature Monitoring using DS18B20

The DS18B20 sensor, as seen in Figure 3, is a digital sensor equipped with an internal 12-bit ADC and is employed for monitoring body temperature. This sensor boasts exceptional accuracy. With a reference voltage of 5V, the smallest detectable change is 5/ (212-1)=0.0012 Volts. The DS18B20 sensor maintains an accuracy of 0.5°C within a temperature range spanning from 10°C to +85°C. Communication with the DS18B20 sensor is established using the 1-Wire (One Wire) protocol, and it is connected to Pin GPIO4 (GPCLK0) on the Raspberry Pi. This sensor will be placed on the fold of the arm.

Fig. 3. Temperature Sensor DS18B20

2.2 Heart Rate Monitoring using Pulse Sensor

A pulse sensor is used for heart rate monitoring. The pulse sensor detects heart rate by measuring fluctuations in the reflected LED signal, which are influenced by the density of blood flow on the skin's surface. The surface of the LED light reflectivity is the skin on the finger. The value of Beats Per Minute (BPM) can be obtained from this sensor. Since the Raspberry Pi lacks an analogue pin, the detection data from the sensor is then received by the Raspberry Pi via the GPIO pin, specifically by adding the ADS1115ADC module as an analogue to digital data converter. The information is entered into BPM. To obtain heart rate information the program gets the peak and the trough values. In the process of getting the BPM value, a threshold is given to get the BPM value from the sensor readings. The determination of this threshold value is based on the sensor output signal which is displayed on the signal plotter when the sensor detects a pulse at the fingertip. These sensors will be mounted at the fingertip, as depicted in Figure 4.

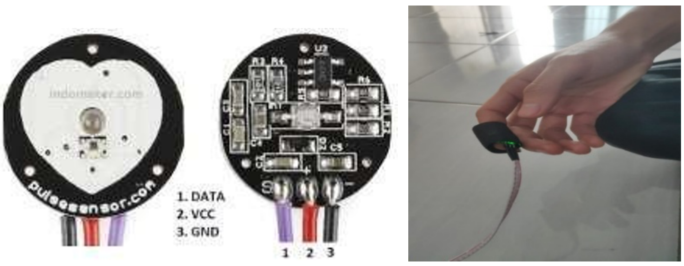

Fig. 4. Pulse Sensor (left) and its placement (right)

2.3 Snore Monitoring

Piezo sensors are used to detect snoring while sleeping. This piezo sensor later is placed on the neck of humans, which is a part of the body that vibrates during sleep when snoring. The vibration of the analogue signal is altered by the piezo sensor in the form of voltage. On the raspberry pi, this analogue signal then is converted to a digital signal. The sensor's output is the number of snoring occurrences per hour (SBI/Hour).

The number of snores in one hour is calculated in the same manner as the BPM value on the pulse sensor. A threshold value is be determined during the data collection process to determine the number of snores from the ADC sensor readings. Because there is no calibrated snoring detection device, this threshold value is determined by comparing the sensor output signal displayed on the signal plotter when the sensor detects a vibration in the neck when snoring occurs with the results of the comparison test of the snore value calculated manually by the operator. The snore sensor will be positioned on the subject's neck to obtain vibration data when the subject snores, as shown in Figure 5.

Fig. 5. Snore Sensor (left) and its placement (right)

2.4 Respiration Rate Monitoring using Piezoelektrik

Piezoelectric sensors are employed to detect respiration through the movement of the diaphragm. When the diaphragm expands, the piezoelectric sensor is compressed by this diaphragmatic movement. This compression generates voltage, which is then read by the Raspberry Pi. Therefore, the sensor is placed around the chest of the test subject, as depicted in Figure 6.

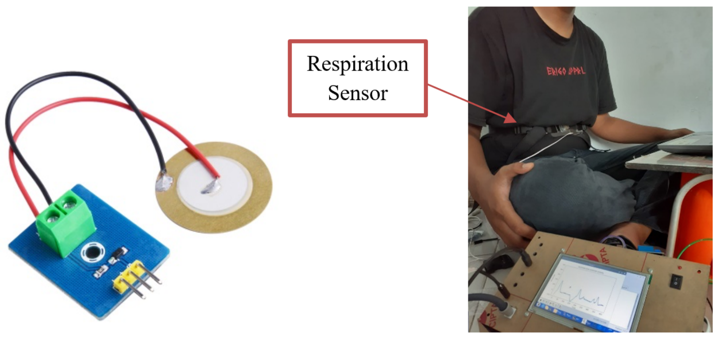

Fig. 6. Respiration sensor (left) and its placement (right)

2.5 GSR Monitoring

The GSR or Galvanic Skin Response sensor is used to measure skin conductivity values. Testing is conducted by placing the GSR sensor electrodes on both fingers, ensuring that the electrodes make contact with the skin on the palm of the hand. The GSR sensor and its placement can be observed in Figure 7.

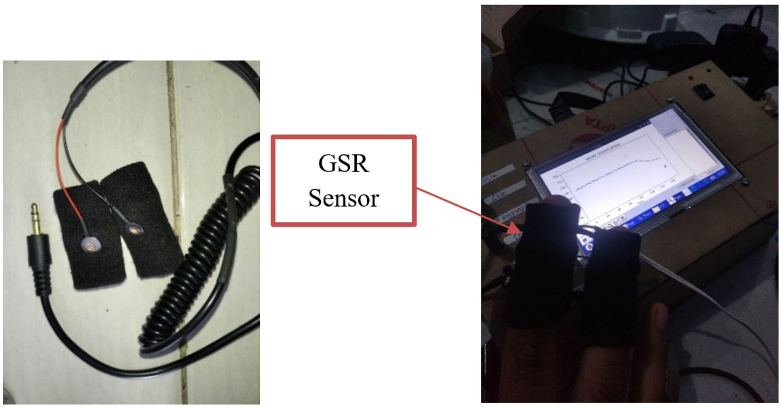

Fig. 7. Respiration sensor (left) and its placement (right)

2.6 Oxygen Saturation using MAX30100

The Max30100 is a sensor capable of measuring oxygen saturation in the body. In arterial blood vessels, oxygen saturation is defined as the ratio of HbO2 (Oxyhaemoglobin) to Hb (deoxyhaemoglobin). HbO2 (Oxyhaemoglobin) is haemoglobin that is fully bound to oxygen. To measure oxygen levels in the blood, an oximeter operates by exploiting the natural pulsation of blood flow in the arteries and the properties of haemoglobin's ability to absorb light. In this process, infrared light is absorbed more by oxygen-rich haemoglobin, while red light is absorbed by haemoglobin lacking oxygen. The values detected are then used to determine the amount of oxygen in the blood. The placement of this sensor is at the fingertip, as shown in Figure 8.

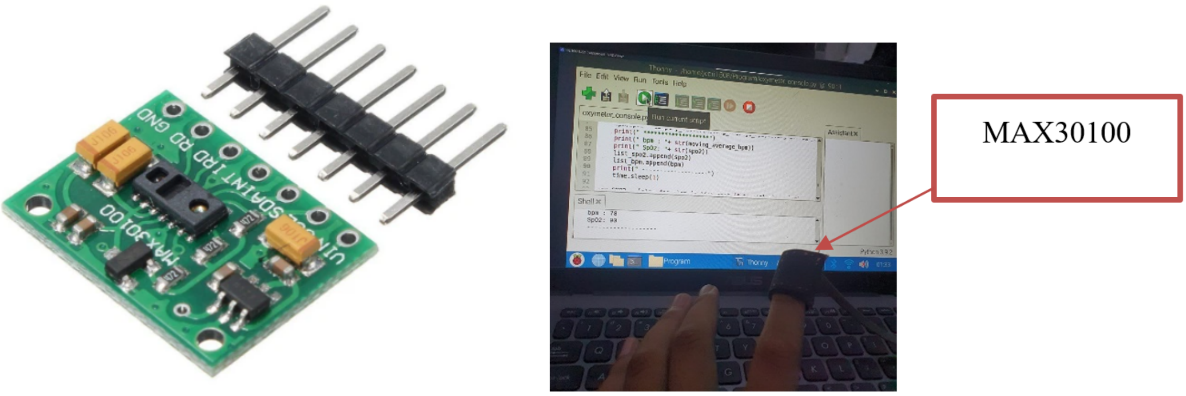

Fig. 8. MAX30100 Module (left) and its placement (right)

2.7 Blood Pressure using MPX5050DP

The blood pressure acquisition device comprises several components, namely the MPX5050DP sensor as the pressure sensor, a motor pump to inflate the cuff with air, a solenoid valve to regulate the release of air from the cuff, and the cuff itself, which is placed on the upper arm of the test subject to obtain blood pressure data. The MPX5050DP sensor and the cuff used can be seen in Figure 9.

Fig. 9. MPX5050DP Pressure Sensor (left) and handcuff (right)

3. Results and Discussion

Figure 10 depicts the Raspberry Pi-based multisensory health monitoring prototype with the sensors employed. These sensors will be simultaneously attached and their data collected from the test subject.

Fig. 10. Prototype Proposed System

3.1 Pulse Sensor Test

The pulse sensor measures heart rate using signal fluctuations caused by blood flow. This sensor is located at the fingertips. The pulse sensor test's accuracy in producing Beat Per Minute (BPM) variables is determined by comparing the sensor's results with heart rate measurements on the OMRON sphygmomanometer, as shown in Figure 11.

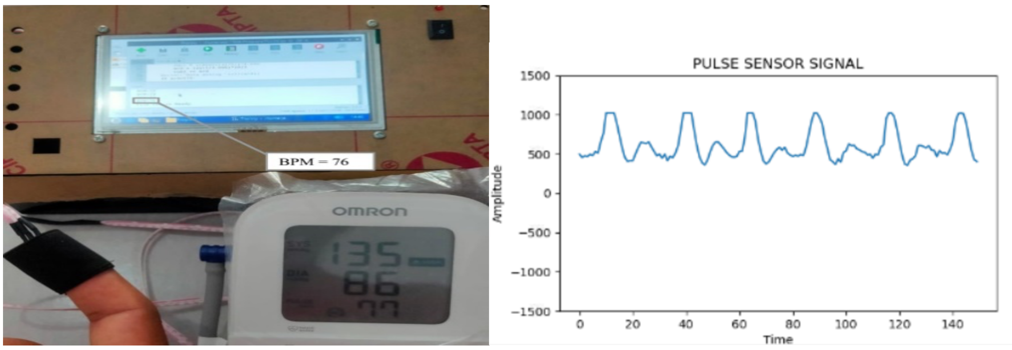

Fig. 11. Pulse Sensor Test and validation using OMRON sphygmomanometer (left) and Output Signal on Pulse Sensor (right)

The resulting signal is shown in Figure 12. Pulse sensor testing was performed on eight test subjects, each of whom was tested three times.

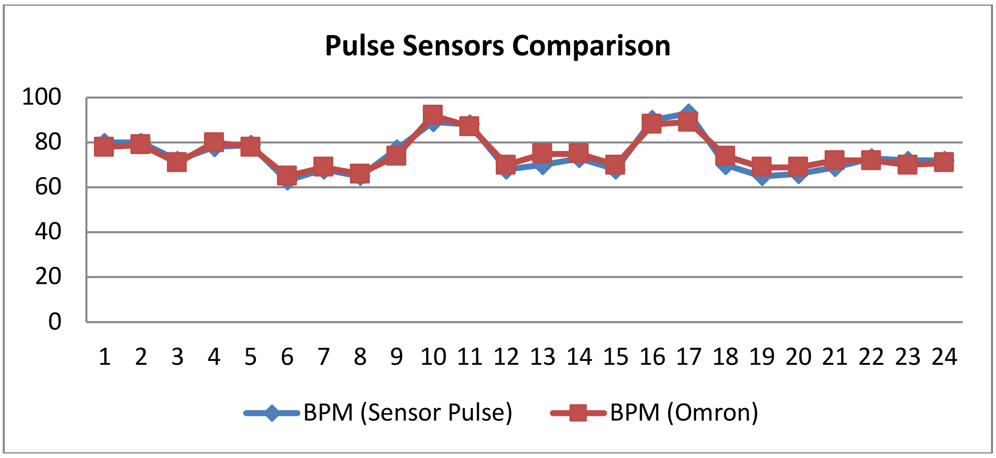

Fig. 12 Comparison of Pulse Sensor Output with OMRON sphygmomanometer

Table 1 shows the results of testing the accuracy of heart rate measurements using the Pulse sensor compared to the OMRON sphygmomanometer.

Table 1
Heart Rate Test Results Accuracy

Subject	BPM (Sensor Pulse)	BPM (Omron)	% Error
	80	78	2.50
1	80	79	1.25
	72	71	1.39
	78	80	2.56
2	79	78	1.27
	63	65	3.17
	68	69	1.47
3	65	66	1.54
	77	74	3.90
	89	92	3.37
4	88	87	1.14
	68	70	2.94
	70	75	7.14
5	73	75	2.74
	68	70	2.94
	90	88	2.22
6	93	89	4.30
	70	74	5.71
	65	69	6.15
7	66	69	4.55
	69	72	4.35
	73	72	1.37
8	72	70	2.78
	72	71	1.39
ERROR RATE			1.05

The smallest error percentage is 0%, and the largest error percentage is 6.15%, according to the results of heart rate testing with a total of 8 test subjects in Table 3. Errors can occur due to noise during the recording of the heart signal as well as an incorrect position of the sensor on the fingertip. The average error rate produced is 1.05%. Figure 6 Illustrates a comparison of data from the pulse sensor output and the results of the OMRON sphygmomanometer measurement.

3.2 Temperature Sensor Test

The DS18B20 temperature sensor data is retrieved continuously for 60 seconds. The reading results then be displayed on the LCD display in degrees Celsius (^oC). Temperature sensor testing was performed on eight subjects, each of whom was tested three times. The sensor readings are compared to those of a calibrated digital thermometer.

Table 2 is the result of the body temperature detection test using the DS18B20 temperature sensor and compared with a digital thermometer. As shown in Table 2, the comparison of the DS18B20 temperature sensor reading with a digital thermometer has the smallest error of 0.1% and the largest error percentage of 2.7%, with the average error of all data collection being 0.259%.

Table 2
Heart Rate Test Results Accuracy

Subject	Temperature (Sensor)	Temperature (Thermometer)	% Error
1	33.53	33.6	0.2083
	34.32	33.9	1.2389
	34.16	34.3	0.4082
2	34.29	34.8	1.4655
	35.82	35.2	1.7614
	35.43	35.3	0.3683
3	34.20	35.1	2.5641
	35.20	35.4	0.5650
	34.50	34.2	0.8772
4	35.88	35.9	0.0557
	34.42	34.4	0.0581
	35.40	35.2	0.5682
5	35.56	35.6	0.1124
	35.32	35.2	0.3409
	35.71	35.8	0.2514
6	35.33	34.4	2.7035
	36.14	36.1	0.1108
	34.94	35.3	1.0198
7	36.12	35.6	1.4607
	34.52	34.56	0.1157
	36.40	35.7	1.9608
8	36.21	36.3	0.2479
	36.28	35.8	1.3408
	36.36	36.2	0.4420
	ERROR RATE		0.259

Figure 13 illustrates a graph comparing the sensor's output temperature data to that of a calibrated digital thermometer.

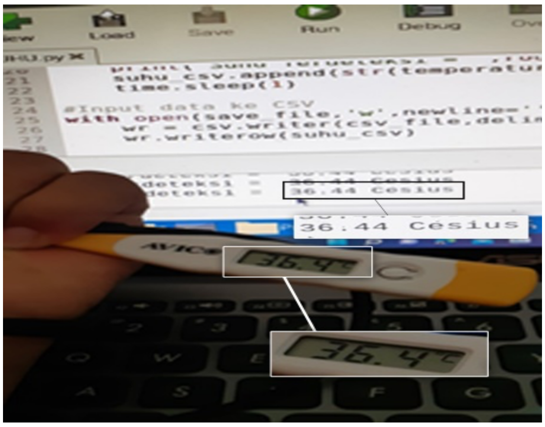

Fig. 13. Hand installation of the Temperature Sensor and direct comparison with a digital thermometer

3.3 Snore Sensor Test

The snore sensor test was performed on five subjects, with each subject collecting data only once. Piezo sensors are very sensitive, so when the sensor's surface is touched, it produces a small voltage that can be seen on the Piezo sensor detection signal plot. A piezo sensor is used in this tool to detect the number of snoring episodes that occur in patients in one hour. When the sensor detects snoring, it generates analogue data in the form of voltage, which is then converted into digital data using an ADC converter. Figure 14 illustrates the snoring sensor output signal.

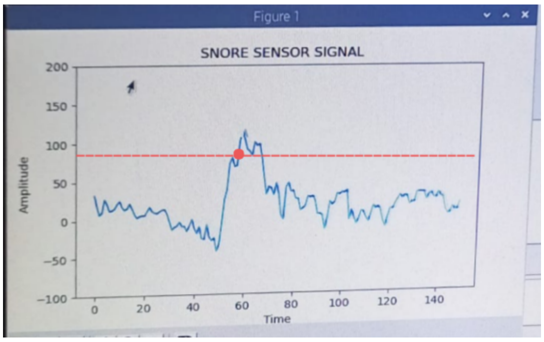

Fig. 14. Output signal of the snore sensor with the red line as the threshold value

The accuracy obtained by comparing sensor snoring calculations to manual calculations is shown in Table 3.

Table 3 shows that the smallest percentage error is 6.48%, while the largest percentage error is 11.11%. The overall data collection error rate is 9.22%. There are several possible causes for the device detecting more snoring than was manually calculated, including the occurrence of neck movement and swallowing activity during data collection, which causes additional vibrations to be detected by the sensor and exceed the specified threshold, causing the sensor to be considered snoring. To improve the accuracy of snoring data collection, better sensors, as well as determining the threshold and separation between snoring and non-snoring, are required.

Table 3
Snoring Sensor Test Results

Subject	Snore (Sensor)	Snore (Manual)	%Error
A	113	102	10.78
B	110	99	11.11
C	115	108	6.48
D	110	103	6.80
E	122	110	10.91
	ERROR RATE		9.22

3.4 Oxygen Saturation Test

Figure 15 represents the data readings from the MAX30100 sensor used and then compared with a calibrated commercial device.

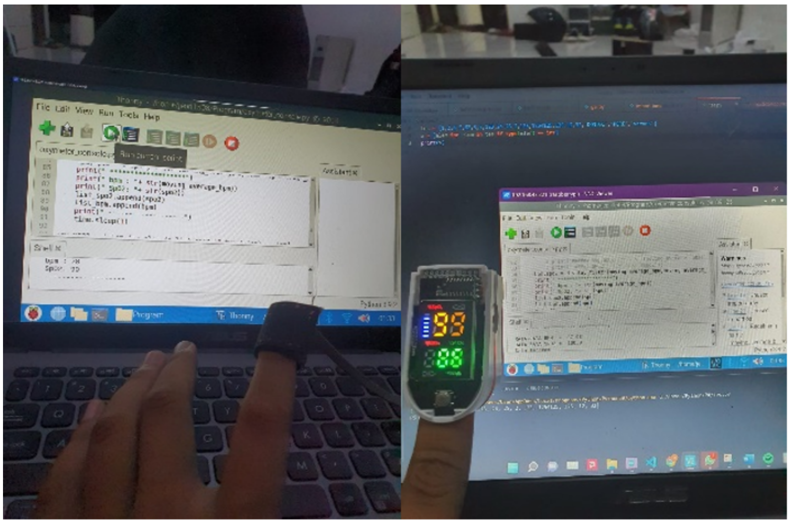

Fig. 15. Oxygen saturation testing (left) and its validation using a commercial oximeter (right)

The test results data is presented in Table 4. It is observed that after conducting 10 measurements, an average error percentage of 2.06% was obtained.

Table 4
Oxygen Saturation Test Results

NO.	Subject	SENSOR MAX30100		ERROR (%)
		MAX30100 SPO2	**Commercial SPO2**	
1	1	100	99	1.01%
2		99	97	2.06%
3	2	98	97	1.03%
4		92	94	2.13%
5	3	100	97	3.09%
6		95	97	2.06%
7	4	100	98	2.04%
8		96	99	3.03%
9	5	100	97	3.09%
10		97	98	1.02%
		Mean Error		2.06%

3.5 Respiration Rate Test

The output signal from the respiration sensor is visible in Figure 16.

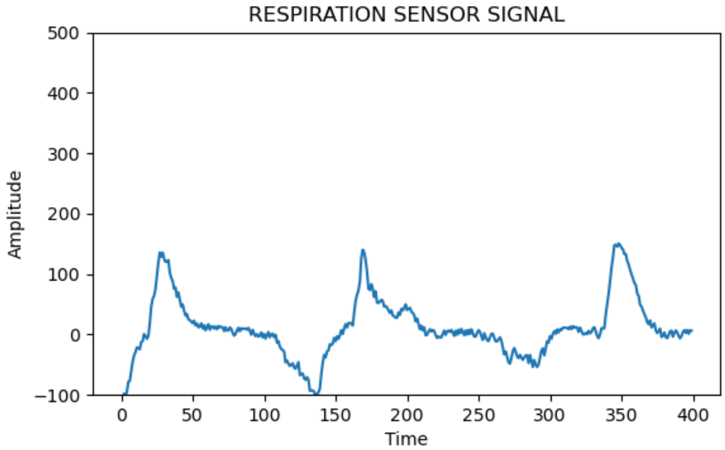

Fig. 16. Respiratory Sensor Signal

The results of the measurement of respiratory frequency in one minute using the piezoelectric sensor and manual calculation are shown in Table 5. It can be seen that the average error percentage from 5 tests is 7.00%. The error occurs due to the presence of noise that arises when the subject is moving or speaking.

Table 5
Respiration Rate Test Results

No	Respiration Sensor	Repiration with manual calculation	Error (%)
1	13	14	7.14
2	16	16	0.00
3	15	13	15.38
4	20	21	4.76
5	12	13	7.69
Mean Error (%)			7.00

3.6 GSR Test

The GSR or Galvanic Skin Response sensor is used to measure skin conductance values. Testing is conducted by attaching GSR sensor electrodes to both fingers, ensuring that the electrodes make contact with the skin on the palm of the hand. GSR measurement is done by comparing the sensor output results in ohms with theoretical skin resistance calculations in ohms, as shown in Table 6. The testing was performed on 4 subjects and repeated for data collection 3 times. The average error obtained from the testing is 0.54%.

Table 6
GSR Test Results and their comparison with theoretical calculations

Subject	ADC Value	Skin Resistance with Sensor (Ω)	Skin Resistance with theoretical calculations (Ω)	Error (%)
1	313	83644	82914.57	0.88
	289	72506.86	71838.56	0.93
	319	86352.92	85567.01	0.92
2	321	87684.84	87225.13	0.53
	333	94922.05	94413.4	0.54
	343	101626.86	101183.43	0.44
3	430	230153.39	229756.09	0.17
	430	230153.39	229756.09	0.17
	428	226060.84	223809.52	1.01
4	395	156905.06	155042.73	1.20
	400	164054.34	162857.14	0.74
	388	145306.02	145161.29	0.10
Mean Error				**0.54**

3.7 Blood Pressure Test

The blood pressure detection circuit consists of the MPX5050dp sensor and a signal conditioning circuit. The MPX5050dp sensor is responsible for acquiring the measured blood pressure data. Blood pressure is the result of blood circulation in the human body. Blood pressure reaches its maximum when the heart contracts to pump blood, known as systolic pressure. When the heart is at rest between two contractions, blood pressure reaches its minimum value, known as diastolic pressure. By applying an air-filled cuff to the arm and inflating it to a certain pressure, the pressure sensor receives pressure signals from the cuff, which are then interpreted as systolic or diastolic pressure through the Raspberry Pi 4B.

Blood pressure measurement tests were conducted on 9 subjects. The measurement results will be compared simultaneously with the results from the commercial OMRON device. The comparison of blood pressure readings between the MPX5050dp sensor and Omron is shown in Table 7, where it can be seen that the average error percentage from 9 tests is 6.63% for systolic readings and 5.53% for diastolic readings.

Table 7
The results of blood pressure testing using the device and the commercial OMRON device

NO.	Blood Pressure (MPX550DP)		Blood Pressure Omron		Error (%)	
	Systolic	Diastolic	Systolic	Diastolic	Systolic	Diastolic
1	120	76	126	79	4.76	3.80
2	128	81	128	80	0.00	1.25
3	126	80	125	82	0.80	2.44
4	119	76	127	78	6.30	2.56
5	136	87	121	78	12.40	11.54
6	119	76	106	75	12.26	1.33
7	142	84	137	84	3.65	0.00
8	115	71	127	84	9.45	15.48
9	125	74	139	82	10.07	9.76
Average Systolic Error					6.63	
Average Diastolic Error					5.35	

4. Conclusion

In this study, seven body signals were monitored with high accuracy, including BPM, body temperature, GSR, blood pressure and oxygen saturation. However, improvements in measuring the amount of snoring and respiration rate are still required. In future work, the already developed wearable sensor will be integrated with data processing using artificial intelligence to become a wearable telemedical health monitoring system capable of predicting various diseases.

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