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Design and Development of a Heart Rate and Blood Oxygen Saturation Monitoring Device in Humans During Sleep Condition Based on the Internet of Things

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Abstract

This research aims to create a heart rate monitoring device (BPM), oxygen saturation (SpO_2), and electrocardiogram (ECG) in IoT-based sleep conditions and connected to Blynk and Telegram. This tool allows monitoring BPM, SpO_2, and ECG values through the LCD screen on the tool or remotely through the Blynk and Telegram applications as IoT media. This research uses engineering methods that involve designing, making tools, testing tools, data collection, and data analysis. The subjects of this research are BPM, SpO_2, ECG, and the application of IoT concepts to monitor remotely and provide real-time notifications. The data analysis technique used is quantitative descriptive analysis with data collection techniques, namely laboratory observation. The conclusion of the results shows that IoT-based monitoring of heart rate and oxygen saturation in human blood has been successfully made using MAX30102 and AD8232 sensors connected to NodeMCU ESP32, as well as LCD to display measurement results. Measurements were made on twelve respondents with varying ages. The measurement was carried out by attaching the tip of the index finger of the left hand to the MAX3012 sensor to obtain BPM and SpO_2 data, and attaching electrodes from the AD8232 sensor to obtain an ECG using the Bipolar lead method. The range of average heart rate measurements is at 65-94 BPM. The average value range of oxygen saturation measurements is at 95%-98%. This tool has an average measurement error value (Error) for heart rate (BPM) of 1.63% and for oxygen saturation (SpO_2) of 2%. The tool also successfully connects Blynk IoT media for Realtime remote monitoring and Telegram application for remote notification media.

Keywords: electrocardiogram, heart rate, internet of things

Introduction

The World Health Organization (WHO) has identified coronary heart disease (CHD) as one of the leading health problems related to the cardiovascular system, with the number of cases increasing rapidly worldwide (Wang et al., 2024; Fan et al., 2024). In Indonesia, national data on the prevalence of heart disease, as recorded by the Ministry of Health through the 2018 Basic Health Research (Riskesdas), showed that as many as 1,017,290 people were diagnosed with heart disease (Simonen et al., 2024). This significant number indicates that heart disease has become one of the top causes of death in the country. Heart attacks, whether occurring for the first time or recurring, can happen under various circumstances—including during sleep (Chen et al., 2024). A person may suffer a heart attack while sleeping due to the narrowing of blood vessels that disrupts blood flow, often caused by the buildup or rupture of arterial plaque in the coronary arteries (Ujjawal et al., 2024). This blockage prevents oxygen-rich blood from reaching the heart, leading to the failure of the heart muscles to pump blood effectively, which typically causes chest pain (Theofilis et al., 2024).

While some individuals are fortunate enough to awaken during the early signs of a heart attack, others are not so lucky. Many people may remain unaware of the symptoms during sleep, resulting in delayed treatment and, tragically, sudden death (Kulzer et al., 2024). A well-known case highlighting this danger is that of Ashraf Sinclair, the husband of Indonesian singer Bunga Citra Lestari, who passed away due to a heart attack in the early hours of February 18, 2020. The cause of death was later confirmed by the family and hospital as cardiac arrest, which occurred during his sleep. This incident underscores the lack of preventive measures and general awareness about the potential for heart attacks to strike while one is asleep. It raises an alarming issue—our physical condition during sleep may go unnoticed, even by those nearby (Knutson, 2024).

In addition to the physiological risks, the lack of accessible, user-friendly technology further compounds the vulnerability of individuals, particularly those with undiagnosed or uncontrolled cardiac conditions (Ishii et al., 2024; Abdelaziz et al., 2024). Most existing cardiac monitoring systems are limited to clinical settings or wearable devices that require conscious use and regular maintenance, making them less effective during unconscious states like sleep (Dang et al., 2024; Zhang et al., 2024). Moreover, in many households, there is limited awareness or preparedness to deal with sudden cardiac events, especially during nighttime when response time is critical (Amro et al., 2024). As such, there is an urgent need for innovative approaches that integrate health monitoring seamlessly into daily life—especially during sleep—without requiring constant user input. The integration of smart sensors with IoT-based alert systems can provide an added layer of security by automatically notifying caregivers or medical services when abnormal cardiac parameters are detected (Madavarapu et al., 2024). This technological advancement holds the potential to shift the paradigm of cardiac care from reactive treatment to proactive prevention, especially for high-risk populations (Salihu et al., 2024).

To address this critical problem, there is a growing need for the development of health monitoring devices capable of detecting vital signs such as heart rate, blood oxygen saturation, and electrocardiogram (ECG) signals. Such technology can provide early warnings when abnormal patterns are detected, enabling timely and appropriate medical intervention. By incorporating real-time monitoring systems, it becomes possible to significantly reduce the risk of undetected cardiac events during sleep and improve patient outcomes through early diagnosis and treatment.

Methods

In this method, engineering techniques are used, which include the stages of tool design, tool fabrication, tool testing, data collection, and data analysis. The stages carried out in the research process are shown in the research flowchart below.

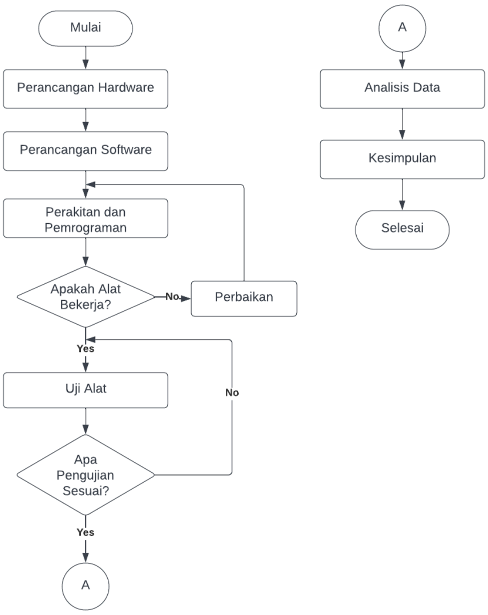


Figure 1. Research Flow Diagram

Figure 1 explains the flow of the research procedure conducted.Starting with the hardware design aimed at finding an efficient combination of devices to use.Followed by software design, then assembly of the device and programming, after creating the program, it is continued with testing the device and data collection.In conducting a system design, input/output planning is also carried out on the system in the device created in this research, which can be shown in the block diagram of the device in Figure 2.

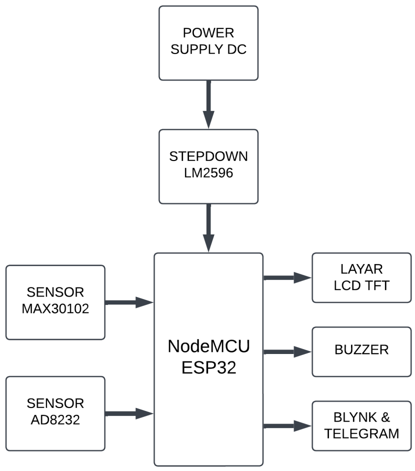


Figure 2, Block Diagram of the Tool

After determining the Input/Output of the tool created, the next step is to design the flowchart of the tool's operation in this research.

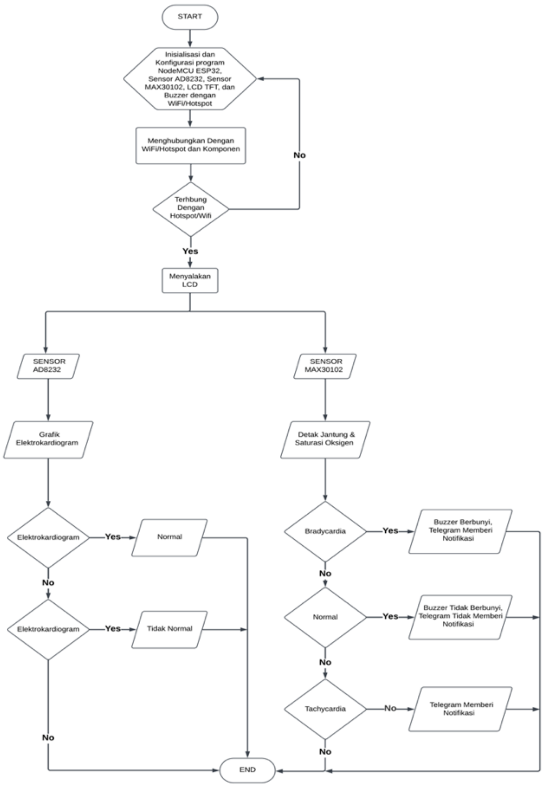


Figure 3. Flowchart of the Tool

Figure 3 is a flowchart of the device that explains the flow of the device's programming, starting from input, process, to the output produced, and will continue to repeat until the device is turned off.The schematic of the circuit within the system is also shown here, where the detailed arrangement of the electrical circuit and components present in the created device is illustrated.

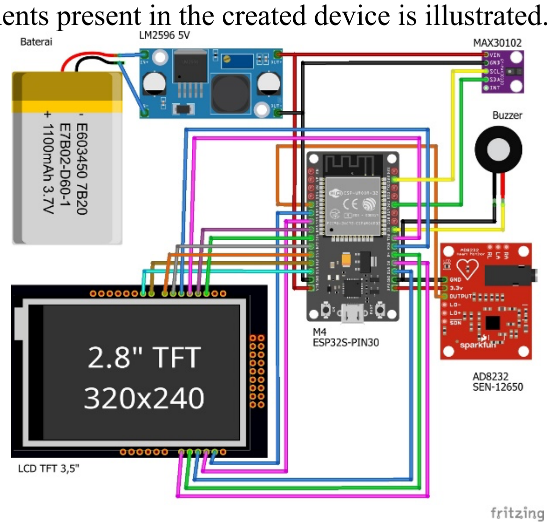


Figure 4. System Circuit Diagram

After the wiring and programming of all components were completed, the shape of the homemade device can be seen in the Figure 5 below.

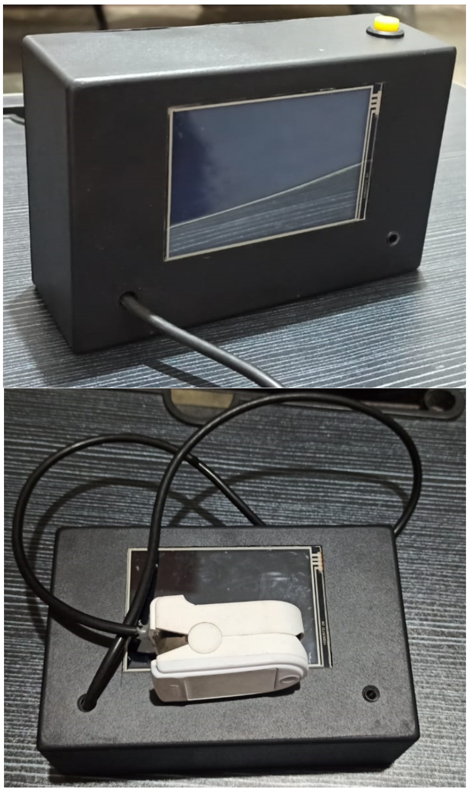


Figure 5. Final Results of the Tool

Results and Discussion

Testing Heart Rate Measurement Using the MAX30102 Sensor

In this test, the calibration of the MAX30102 sensor is performed by comparing the homemade device with the Fingertip Pulse Oximeter Lk88 so that the reading differences can be calculated according to the actual value of the device.

Table 1. Testing Heart Rate Measurement Using the MAX30102 Sensor

No.	Time	Handmade Device (BPM)	Pulse Oximeter (BPM)	Reading Difference	Error (%)
1.	18.14	89	90	1	1.1%
2.	18.18	85	85	0	0%
3.	18.24	82	83	1	1.1%
4.	18.26	89	85	4	4.7%
5.	18.30	81	83	2	2.4%
6.	18.34	86	87	1	1.1%
7.	18.38	82	83	1	1.1%
8.	18.42	79	81	2	2.4%
9.	18.46	83	85	2	2.4%
10.	18.50	81	81	0	0%
Average Error %					1.63%
Accuracy %					98.37%

Table 1 presents the heart rate measurement data from the MAX30102 sensor using the Photoplethysmography method, conducted on the left index finger, compared with the Fingertip Pulse Oximeter Lk88.Where the heart rate values measured by the MAX30102 sensor and the Lk88 Oximeter are calculated for their differences and measurement error values.Based on the data in Table 1, the average measurement error value is obtained at 1.63% and the heart rate measurement accuracy is obtained at 98.37%.

Testing Oxygen Saturation Measurement Using the MAX30102 Sensor

In this test, the calibration of the MAX30102 sensor was conducted by comparing the homemade device with the Pulse Oximeter Fingertip Lk88 so that the reading differences could be calculated according to the actual value of the device.

Table 2. Testing Oxygen Saturation Measurement Using the MAX30102 Sensor

No.	Time	Time	Handmade Device (BPM)	Pulse Oximeter (BPM)	Reading Difference
1.	18.14	96	98	2	2.%
2.	18.18	95	99	4	4%
3.	18.24	97	99	2	2%
4.	18.26	94	99	5	5%
5.	18.30	97	99	2	2%
6.	18.34	98	99	1	1%
7.	18.38	98	99	1	1%
8.	18.42	97	98	1	1%
9.	18.46	98	99	1	1%
10	18.50	98	99	1	1%
Average Error %					2%
Accuracy %					98%

Table 2 presents the data from the measurement of oxygen saturation using the MAX30102 sensor with the Photoplethysmography method, conducted on the left index finger, compared with the Fingertip Pulse Oximeter Lk88.The oxygen saturation values measured by the MAX30102 sensor and the Lk88 Oximeter were calculated for their differences and measurement error values.Based on the data in Table 2, the average measurement error value is 2%, resulting in an oxygen saturation measurement accuracy of 98%.

Testing the Measurement of Electrocardiogram Graphs

Testing of electrocardiogram measurements using the bipolar lead method on the right chest, left chest, and right abdomen to display the electrocardiogram graph on the LCD of the heart rate and oxygen saturation monitoring device in sleep conditions based on IoT.

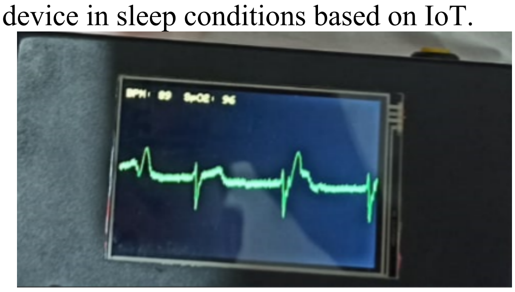
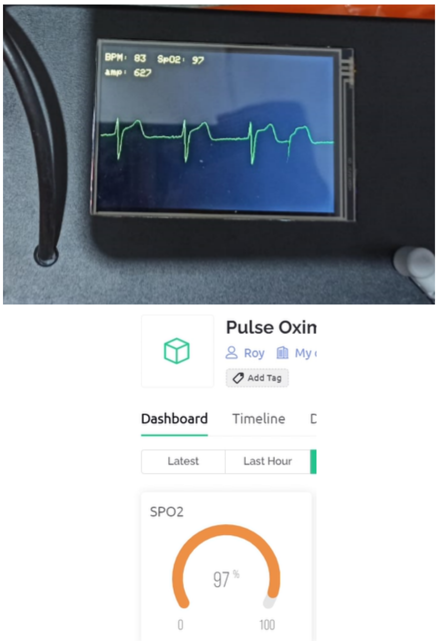


Figure 6. Testing the Electrocardiogram Graph Measurement

Figure 6 shows the display of the electrocardiogram graph from the AD8232 sensor on the LCD of the heart rate and oxygen saturation monitoring device in an IoT-based sleep condition. After testing the electrocardiogram graph, it was found that the graph could be displayed on the screen and continuously updated every 5 milliseconds. However, the displayed graph sometimes still includes ripples or noise due to the instability of the connecting cable from the chest to the AD8232 sensor.

Testing Heart Rate and Oxygen Saturation Monitoring on LCD and Blynk Application

This test was conducted by recording and comparing in real-time the heart rate and oxygen saturation values displayed on the LCD monitor and the Blynk Application. The purpose of this test is to determine the device's ability to transmit heart rate and oxygen saturation data in real-time.



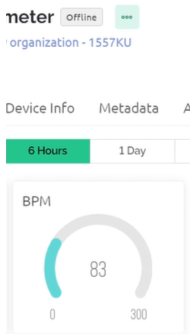


Figure 7. Testing Heart Rate and Oxygen Saturation Monitoring Values on LCD and Blynk Application

In Figure 7, there are heart rate and oxygen saturation values displayed on the device's LCD monitor and the Blynk application, thus obtaining the values when the device sends heart rate data until it is displayed on the Blynk application.Based on the measurement data from ten trials, there is a very good agreement with an error rate of 0%.This indicates that there is no delay when the device transmits heart rate data to the Blynk Application.

Testing Notification Monitoring on the Telegram Application

This test was conducted by observing notifications in real-time on the Telegram application. The purpose of this test is to determine the device's ability to send notification data in real-time.

Table 3. Notification Monitoring Testing on the Telegram Application

No.	Time	Notification	Status
1.	15.38	Perhatian! Nilai Detak Jantung Naik Di Atas 100 BPM, Silakan Cek Kondisi Pengguna. 15:38 Perhatian! Nilai Detak Jantung Naik Di Atas 100 BPM, Silakan Cek Kondisi Pengguna. 15:39	succeeded
2.	15.41	Perhatian! Kadar Oksigen Turun Di Bawah 95%, Silakan Cek Kondisi Pengguna. 15:41	succeeded
3.	15.45	Perhatian! Kadar Oksigen Turun Di Bawah 95% Dan Detak Jantung Turun Di Bawah 60 BPM, Silakan Cek Kondisi Pengguna. 15:45	succeeded
4.	17.29	Perhatian! Kadar Oksigen Turun Di Bawah 95%, Silakan Cek Kondisi Pengguna. 17:29	succeeded
5.	17.43	Perhatian! Nilai Detak Jantung Naik Di Atas 100 BPM, Silakan Cek Kondisi Pengguna. 17:43	succeeded
6.	17.51	Perhatian! Nilai Detak Jantung Turun Di Bawah 60 BPM, Silakan Cek Kondisi Pengguna. 17:51	succeeded
7.	17.54	Perhatian! Kadar Oksigen Turun Di Bawah 95%, Silakan Cek Kondisi Pengguna. 17:54	succeeded
8.	22.02	Perhatian! Kadar Oksigen Turun Di Bawah 95%, Silakan Cek Kondisi Pengguna. 22:02	succeeded
9.	22.07	Perhatian! Kadar Oksigen Turun Di Bawah 95%, Silakan Cek Kondisi Pengguna. 22:07	succeeded
10.	22.22	Perhatian! Kadar Oksigen Turun Di Bawah 95%, Silakan Cek Kondisi Pengguna. 22:22	succeeded

Based on the data in table 3, it is known that notifications from the device can be sent successfully to the Telegram application, so the notification system on the device can be said to have been successfully implemented with the predetermined reference parameters.

Collection of Respondents' Heart Rate Data

This data collection is a test conducted by measuring the heart rate values displayed on the LCD screen of the heart rate and blood oxygen saturation detector in humans during sleep conditions based on IoT.This data collection was conducted repeatedly ten times within a constant three-minute interval for twelve respondents, resulting in the average heart rate of the twelve respondents in Table 4 below.

Table 4. Testing Respondents' Heart Rate Data

No	Name	Age	Heart Rate (BPM)										Average Heart Rate
1	Roy Oktaf Fiyanto	22	89	85	82	89	81	86	82	79	83	81	84
2	Tariyanto	53	60	73	70	79	77	55	69	60	55	56	65
3	Rheza	22	91	97	100	88	96	99	89	98	85	96	94
4	Arioseno	22	98	80	83	72	103	71	84	85	85	77	84
5	M. Nurdin	17	87	84	71	70	89	87	72	94	93	80	83
6	Arsyl	16	85	89	88	79	85	100	95	83	76	81	86
7	Abdul Haris	55	74	90	85	90	89	94	96	92	93	90	89
8	Purnomo	22	90	86	89	90	98	93	84	90	90	86	87
9	Ahmad	22	87	98	95	94	97	93	92	96	99	86	94
10	Rezkiana	23	77	85	81	88	73	85	82	75	85	86	82
11	Fajar	22	66	82	74	67	74	66	70	77	64	61	70
12	Habibie	21	88	70	66	64	65	60	77	70	61	67	69

Based on Table 4 above, the results of the average heart rate test on twelve respondents are shown in the graph below.

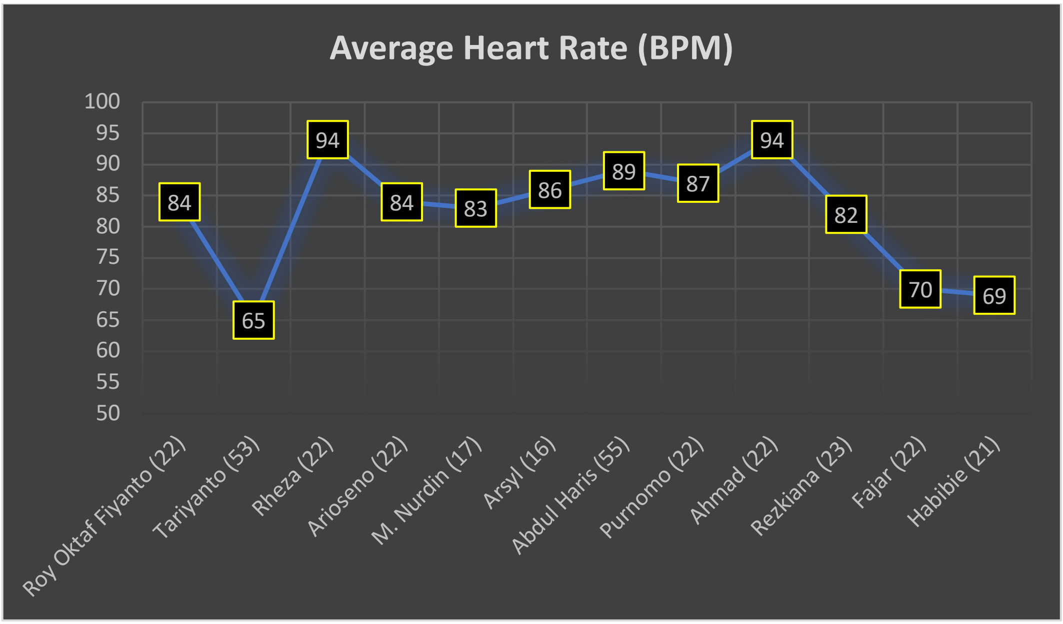


Figure 8. Average Heart Rate (BPM) Graph

In the average heart rate graph, the displayed data are relatively in normal condition for the twelve respondents aged 16-55 years, ranging from 65-94 BPM.This is because at the time of data collection, the respondents' health conditions were in good condition.The author also found one respondent who had the lowest average heart rate among the other twelve respondents, namely Mr. Tariyanto, who had an average heart rate of 65 BPM.

Collection of Respondents' Oxygen Saturation Data

This data collection is a test conducted by measuring the oxygen saturation value displayed on the LCD screen of the heart rate and blood oxygen saturation detector device in humans during sleep conditions based on IoT.This data collection was conducted repeatedly ten times within a constant three-minute interval for twelve respondents, resulting in oxygen saturation data for the twelve respondents in Table 5 below.

Table 5. Testing Respondents' Oxygen Saturation Data

No	Name	Age	Oxygen Saturation (%)										Average Oxygen Saturation
1	Roy Oktaf Fiyanto	22	96	95	97	94	98	98	97	98	98	98	97
2	Tariyanto	53	98	98	98	98	99	98	98	98	98	98	98
3	Rheza	22	97	97	97	97	97	98	97	97	97	97	97
4	Arioseno	22	96	95	96	98	95	96	97	96	97	98	96
5	M. Nurdin	17	97	97	97	96	95	96	93	96	94	94	95
6	Arsyl	16	94	96	95	93	94	97	97	97	96	97	96
7	Abdul Haris	55	97	98	97	97	97	96	97	97	97	96	97
8	Purnomo	22	98	97	96	97	98	98	98	96	98	96	97
9	Ahmad	22	97	93	97	96	97	97	94	97	96	96	96
10	Rezkiana	23	96	96	95	97	97	99	97	96	97	95	96
11	Fajar	22	85	90	96	97	94	98	99	96	97	98	95
12	Habibie	21	97	94	96	90	97	94	97	95	96	96	95

Based on Table 5 above, the results of the average oxygen saturation test on twelve respondents are shown in the graph below.

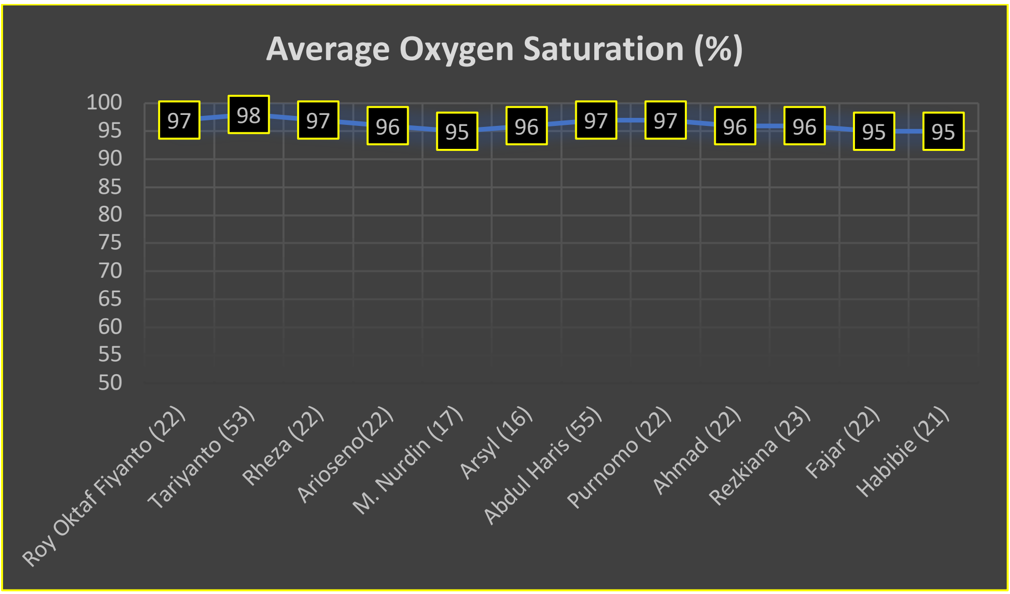


Figure 9. Average Oxygen Saturation Graph of Respondents

In the graph of average oxygen saturation values, the data displayed is relatively different under normal conditions for the twelve respondents aged 16-55 years, ranging from 95-98%.This is because at the time of data collection, the respondents' health conditions were in good condition.

Conclusion

The Heart Rate and Blood Oxygen Saturation Monitor for Humans During Sleep Based on the Internet of Things can be used to determine heart rate (BPM) and oxygen saturation (SpO2) values by utilizing the MAX30102 sensor, with an accuracy value of 98.37% for heart rate (BPM) measurements and 98% for SpO2 measurements.The Heart Rate and Blood Oxygen Saturation Monitor for Humans During Sleep Based on the Internet of Things can be used to obtain an electrocardiogram (ECG) graph by utilizing the AD8232 sensor. The graph can be displayed on an LCD screen and continuously updated every five milliseconds. However, the displayed graph sometimes still includes ripples or noise due to the instability of the connecting cable from the chest to the AD8232 sensor.The Heart Rate and Blood Oxygen Saturation Monitor for Humans During Sleep Based on the Internet of Things can connect with Internet of Things media such as Blynk and Telegram to monitor heart rate, oxygen saturation, and provide remote notifications in real-time.

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