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Heart Rate and Oxygen Saturation Internet of Things System (HROS-IoT) Uses Fuzzy Logic

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Abstract

Emergencies in hospitals, including in-hospital cardiac arrest (IHCA), necessitate effective response systems for monitoring vital signs such as heart rate and oxygen saturation. This study aims to develop and evaluate a Heart Rate and Oxygen Saturation Internet of Things (HROS-IoT) system utilizing the MAX30102 sensor and ESP32 microcontroller for real-time health monitoring. The system transmits data to the Blynk application via WiFi, enabling remote monitoring. Testing involved comparing the HROS-IoT system's performance against the commercial LK87 oximeter in measuring heart rate and oxygen saturation before and after meals with five participants. Results indicated that the HROS-IoT system produced heart rate measurements with an average error of 5.2 BPM before meals and 11.3 BPM after meals. Oxygen saturation readings showed an average error of 1% before meals and after meals. Despite minor discrepancies influenced by individual physiological differences and environmental conditions, the HROS-IoT system consistently delivered reliable data. The system's real-time monitoring capability and remote data access enhance proactive health management in hospitals. This study demonstrates the potential of the HROS-IoT system to improve patient outcomes and safety, suggesting further refinements for better accuracy and integration into healthcare settings.

A. Introduction

According to the Decree of the Minister of Health of the Republic of Indonesia Number 432/MENKES/SK/IV/2007, emergencies can occur in hospitals[1]. An emergency is an event that can cause death or serious injury to workers, visitors, or the public, disrupt business activities, operations[2], cause physical environmental damage, or threaten the hospital's finances and reputation[3][4]. As part of hospital occupational health and safety management, an Emergency Response System is absolutely necessary . Emergencies can happen anywhere and anytime[5], and those working in the health sector are responsible for handling these situations[6] . One type of life-threatening emergency if not handled immediately is in-hospital cardiac arrest (IHCA). Cardiac arrest is a condition where the heart's beating is insufficient to meet the oxygen needs of the brain and other vital organs quickly [7][8][9]. The heart rate, measured in Beats per Minute (BPM), is an indicator of heart condition[10]. A range of 60 to 100 BPM is considered normal for the human heart [11][12][13]. The normal oxygen saturation percentage in humans, consistent across all ages, is 95% to 100%, whether for newborns or the elderly[14]. The management of cardiac arrest aims to prevent brain death and permanent death by quickly and accurately detecting and acting to restore the heartbeat to normal levels as soon as possible[15] .According to Holmberg et al., there are 292,000 cases of In-Hospital Cardiac Arrest (IHCA) annually in adults in the United States and 15,200 IHCA cases in pediatric hospitals [16]. Enrollment began on July 1, 2019, and ended on January 1, 2020. 35,451 IHCAs had been enlisted in all participating hospitals by December 31, 2020[17]. There were 159 IHCAs among 152 patients, with 66.4% being male and the average age being 70.2 years (± 13.9)[18].

Among the clinical signs usually examined in hospitals, heart rate and oxygen saturation are the most important[19][20]. In this process, some hospitals still use manual systems to check heart rate and oxygen levels, requiring nurses to visit patient rooms to observe and record both[21][22][23]. This must be done regularly to avoid endangering the patient. Due to negligence in monitoring or even ignorance of whether the patient's condition is normal, delayed treatment can be dangerous for the patient[24][25]. Patients will experience IHCA if not treated immediately.

The modern digital life, where everything can be done quickly and information can be shared in seconds, marks the Industrial Revolution 4.0[26][27][28]. Due to human interest in technological products that make work easier, today's technology is rapidly advancing . This includes artificial intelligence, Cloud Computing, big data analytics, cybersecurity, and the Internet of Things[29][30]. The internet has evolved from static document storage to a vast world of connected users, devices, and applications, increasing internet usage by 25% today, according to McKinsey data[31]. The Internet of Things (IoT) is a network of connected devices that enables communication processes between sensors, actuators, operating systems, microcontrollers, communication technologies, security, IoT platforms, and analytical tools. The working system of IoT technology is to process and transmit digital information from sensor equipment such as GPS systems, infrared sensors, and radio frequency identification (RFID) [32].

Control and display via phone are conducted through the Blynk application, which is connected to the setup via Wi-Fi. Blynk is downloadable software that provides an easy-to-use platform for users to control devices and receive outputs.

Authentication for using Blynk is done through a code sent to the user's email during configuration. This code can then be shared with other users to authorize access. shared with other users to authorize access.

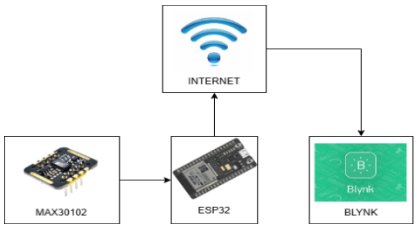


Figure 1. Tool Design

B. Materials and Methode

This device design revolves around the utilization of ESP32 as the main microcontroller, paired with the MAX30102 sensor for detecting heart rate and oxygen saturation (FIGURE 1). The integration of ESP32 with MAX30102 allows users to monitor critical health parameters such as heart rate and oxygen saturation in real-time.For enabling monitoring via mobile phones, an additional application installed on the phone, namely the Blynk application, is required. By installing the Blynk application on the phone, users can easily access heart rate and oxygen saturation data remotely, providing greater flexibility and accessibility in health monitoring.

Connectivity to the internet is a crucial prerequisite for the functionality of this device. Internet signal can be obtained through a WiFi connection or a mobile phone hotspot. This ensures that users can stay connected and access health data directly, even when they are in different locations.To connect the device to the Blynk application, users only need to use the unique code received via email, along with providing the corresponding SSID and WiFi password. With these simple steps, users can quickly connect their device to the Blynk application and start monitoring their health effortlessly.

C. How The Tool Works

The tool used works by combining several main components to monitor heart rate and oxygen saturation effectively. First, the MAX30102 sensor is used to detect vital signals from the body, such as heart rate and oxygen levels in the blood. This sensor uses photoplethysmography (PPG) technology to measure changes in light that occur when blood flows through blood vessels. The data collected by the MAX30102 sensor is then forwarded to the ESP32 microcontroller for further processing. The ESP32 is responsible for data processing, including the calculation of heart beats per minute (BPM) and the percentage of oxygen saturation in the blood (SpO2). After the data is processed, the results are sent to the Blynk platform via the internet network. The Blynk platform allows users to monitor and access their health information remotely via an app installed on their smartphone. Thus, this tool not only provides accurate monitoring, but also allows easy and convenient access to the user's health information. In making a HROS-IoT some supporting hardware is needed. The hardware needed is :

Table 1. Hardware

No	Device	Tota l	Description
1	MAX 30102	1	As a sensor
2	ESP 32	1	As a microcontroller
3	Board	1	To place the tool circuit
4	Jumper Cable	4	To connect the tool
5	Laptop	1	Used for tool configuration
6	Mobile phones	1	As an additional device for monitoring

This application requires consideration of both software and hardware. Software is necessary for hardware operation. The following software was utilized in the study is:

Table 2. Software

No	Device	Description
1	Arduino IDE	As software for writing programs, compiling programs, and uploading programs
2	Blynk	As software that resides on mobile phones for monitoring with the concept of Internet of Things
3	Library Wire.h	Used for I2C communication
4	Library WiFi.h	Used to connect ESP32 to a Wi-Fi network
5	Library BlynkSimpleESP32.h	To connect ESP32 to the Blynk
6	Library WidgetRTC.h	Used in conjunction with the Blynk to provide RTC functionality
7	Library MAX30105.h	Used to interface with the MAX30102 sensor
8	Library heartRate.h	To process the raw data from sensor and calculate heart rate

In designing this program, it was created using the Arduino programming language which is embedded in the ESP32. The aim is that the tool components used can carry out commands that match the purpose of the tool being designed as in the image below.

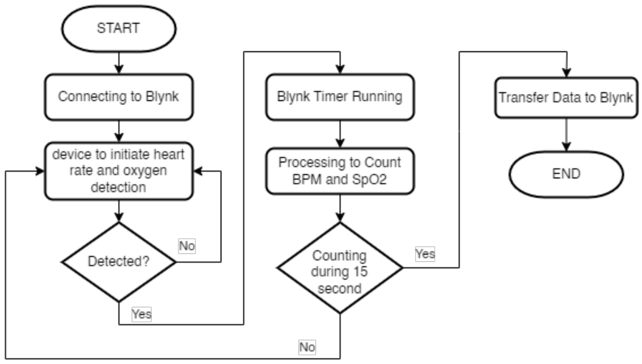


Figure 2. Flowchart System

The image above is the programming algorithm for the system to be built. This system starts from connecting the connection to Blynk. If it is connected, the tool will detect whether there is a pulse on the wrist. When a pulse is detected, Blynk will start a timing operation (timer). During this operation, the tool calculates the number of heart beats per minute (BPM) and the percentage of oxygen saturation (SpO2). When the calculation reaches 15 seconds, the data is sent to Blynk.
This algorithm is designed to ensure that the data sent to Blynk is accurate and up to date. By detecting wrist pulses before starting calculations, the system can avoid erroneous readings caused by sensor interference or errors. The use of timers allows data to be collected periodically, ensuring that each measurement covers a sufficient period to produce representative values. After 15 seconds, heart rate and oxygen saturation data are sent to Blynk, providing users with near real-time information about their health condition. The implementation of these algorithms increases the reliability and effectiveness of the monitoring system, making it a useful tool for personal health monitoring.

D. Result

In discussing these results, testing and discussion were carried out regarding the performance of the HROS-IoT, by monitoring heart rate and oxygen saturation between the system that has been created with the LK87 oximeter. Measurements are taken simultaneously on different fingers. The use of the LK87 oximeter is used as a comparative measuring tool for the system created because the LK87 oximeter is capable of measuring heart rate and oxygen saturation which has been calibrated by the factory and has been used commercially in the community.

Figure 3. Testing The Device

The testing takes place before and after meals. This test uses 20 people as samples. The heart rate and oxygen saturation are recorded after 1 minute since the system and the LK87 oximeter began measuring the samples heart rate and oxygen saturation.

Table 3. Hearth Rate Data

Name	Age	Before Eating		After Eating	
		HROS-IoT (BPM)	LK87 (BPM)	HROS-IoT (BPM)	LK87 (BPM)
Revanza	20	94	96	116	102
Bagus	20	78	78	91	85
Farhan	20	90	90	108	102
Farida	69	72	74	88	94
Karmini	57	65	63	68	72
Rini	44	84	86	98	102
Linceria	63	74	73	77	73
Dewi	39	81	81	73	88
Akhirda	52	79	80	50	102
Novianti	34	84	86	96	86
Dewi	39	81	81	87	89
Nila	41	95	90	80	89
Tri	49	95	115	82	115
Meta	51	56	75	88	82
Tansimah	62	63	87	85	95
Ari	50	84	81	116	104
Ria	36	77	90	84	90
Ida	53	90	88	61	68
Fina	55	90	88	89	88
Nurlela	61	94	90	90	108
Average Error		5.2 BPM		11.3 BPM	

Heart rate is calculated based on the time interval between the last two beats detected by the infrared sensor (IR). The formula for calculating Beats Per Minute (BPM) is:

$$BPM = \frac{60}{\frac{delta}{1000}} \qquad (1)$$

Where:

Delta is the time difference in milliseconds between the last two beats.

The average BPM is calculated by taking the average of the BPM values stored in an array. Assuming we have an array of BPM values as rates[i] where [i] is the index:

$$Avg\ BPM = \frac{\sum_{i=0}^{N} rates[i]}{N} \qquad (2)$$

Where N is the number of elements in the array (in this case, 4).

Based on the data obtained from testing with the HROS-IoT system and LK87 oximeter on 5 samples of varying ages, it was discovered that there are changes in heart rate measurements before and after meals. Specifically, the HROS-IoT system produces greater heart rate data than the LK87 oximeter, particularly after meals. The typical variation in heart rate before meals is about 5.2 BPM, while the difference after meals is around 11.3 BPM. However, individual physical circumstances, sensor qualities, and environmental conditions during measurement can all impact these disparities.

Table 4. Saturation Oxygen Data

Name	Age	Before Eating		After Eating	
		HROS-IoT (%)	LK87 (%)	HROS-IoT (%)	LK87 (%)
Revanza	20	96	96	95	96
Bagus	20	97	97	97	96
Farhan	20	96	96	96	96
Farida	69	98	98	95	97
Karmini	57	96	95	97	95
Rini	44	99	97	96	97
Linceria	63	96	96	97	96
Dewi	39	98	99	96	98
Akhirda	52	96	96	96	96
Novianti	34	97	96	97	96
Dewi	39	97	97	98	97
Nila	41	96	95	96	96
Tri	49	99	97	97	98
Meta	51	96	96	96	96
Tansimah	62	96	95	96	96
Ari	50	96	95	96	95
Ria	36	95	98	97	96
Ida	53	96	97	96	97

Name	Age	Before Eating		After Eating	
		HROS-IoT (%)	LK87 (%)	HROS-IoT (%)	LK87 (%)
Fina	55	97	99	99	97
Nurlela	61	97	95	97	95
Average Error		1 %		1 %	

Oxygen saturation is calculated based on the ratio between the red LED value (redValue) and the infrared LED value (irValue). The formula used is:

$$SpO2 = 104 - 25\ X\ (\frac{redValue}{irValue})\ (3)$$

Additional Conditions:

- To calculate BPM, δ\deltaδ must be a reasonable value for human heartbeats (20 < BPM < 255).
- To calculate SpO2, irValue must be greater than 50000, indicating a finger is on the sensor.

Based on the data provided for heart rate measurements before and after meals utilizing the HROS-IoT system and LK87 oximeter on 5 samples of various ages, the following conclusions can be drawn. The average error in saturation oxygen measurements before meals and after meals between the HROS-IoT system and the LK87 oximeter is around 1%.

These data imply that, while both systems produce similar heart rate measurements, the HROS-IoT system tends to register slightly higher values, particularly after meals. Individual physiological variances, sensor properties, and testing environmental conditions may all have an impact on these discrepancies.

Calculating Beats Per Minute (BPM)

The formula used to calculate BPM is:

$$BPM = \frac{60x1000}{\Delta Millis} \quad (4)$$

Analysis:

- Δ Millis the time difference in milliseconds between the last two beats detected by the sensor.
- **60**: Conversion factor from seconds to minutes.
- **1000**: Conversion factor from milliseconds to seconds.

This formula determines the heart rate by measuring the interval between consecutive heartbeats. A smaller interval results in a higher BPM, and vice versa.

Average BPM (Avg BPM)

The formula for calculating the average BPM is:

$$Avg\ BPM = \frac{\sum_{i=0}^{N-1} BPMi}{N} \qquad (5)$$

Analysis:

- BPMi : BPM value from the i-th measurement.
- N: Number of measurements, in this case, 4.

Calculating the average BPM helps to obtain a more stable value and reduces temporary variations in heart rate that may be caused by movement or other disturbances.

Calculating Oxygen Saturation (SpO2)

The formula for calculating the average SpO2 is:

$$SpO2 = 104 - 25\ X\ (\frac{redValue}{irValue}) \qquad (6)$$

Analysis:

- redValue: of the red LED detected by the sensor.
- irValue: Value of the infrared LED detected by the sensor.
- 104: Constant value used in SpO2 calculation.
- **25**: Coefficient used to compute the ratio between red and infrared LEDs.

This formula is based on the principle that oxygenated blood absorbs less red light than infrared light. Thus, the ratio of red to infrared light can estimate the level of oxygen saturation in the blood.

Static analysis and chart Before Eating :

```
# Statistik Deskriptif
mean_hr = df['Heart Rate (bpm)'].mean()
median_hr = df['Heart Rate (bpm)'].median()
std_hr = df['Heart Rate (bpm)'].std()

mean_spo2 = df['Saturasi Oksigen (%)'].mean()
median_spo2 = df['Saturasi Oksigen (%)'].median()
std_spo2 = df['Saturasi Oksigen (%)'].std()

print(f"Rata-rata HR: {mean_hr}, Median HR: {median_hr}, Standar Deviasi HR: {std_hr}")
print(f"Rata-rata SpO2: {mean_spo2}, Median SpO2: {median_spo2}, Standar Deviasi SpO2: {std_spo2}")
```

```
Rata-rata HR: 80.7, Median HR: 80.5, Standar Deviasi HR: 9.440456674452895
Rata-rata SpO2: 96.6, Median SpO2: 96.0, Standar Deviasi SpO2: 1.1737877907772671
```

Figure 4. Static Analysis Before Eating

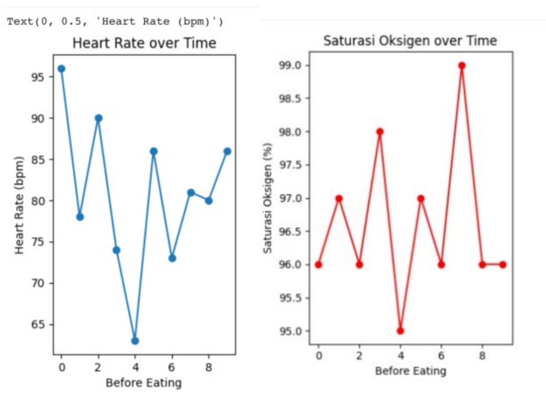
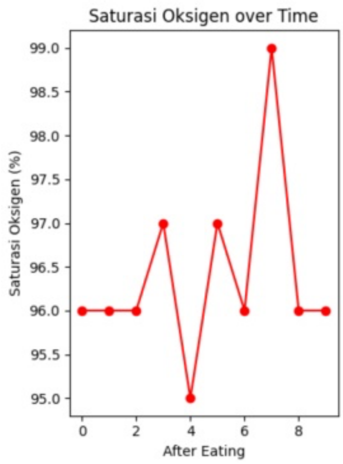


Figure 5. Chart Before Eating



From the results of static analysis of heart rate (HR) and oxygen saturation (SpO2) before eating, it was found that the average HR was 80.7 bpm with a median HR of 80.5 bpm. This shows that the heart rate before eating is relatively stable and symmetrical. The HR standard deviation of 9.44 bpm indicated some fluctuations in heart rate, but these fluctuations were not significant. For SpO2, the average was 96.6% with a median of 96.0%, indicating that oxygen saturation was within a healthy and stable range. The low SpO2 standard deviation of 1.17% indicates that oxygen saturation values are very consistent with little variation between measurements. In conclusion, both heart rate and oxygen saturation before meals were within the normal and healthy range, indicating good health conditions in the individuals measured. However, it is important to continue to monitor HR and SpO2 periodically to ensure these values remain within the normal range and to immediately consult a medical professional if significant changes occur.

Static analysis and chart After Eating :

```
# Statistik Deskriptif
mean_hr = df['Heart Rate (bpm)'].mean()
median_hr = df['Heart Rate (bpm)'].median()
std_hr = df['Heart Rate (bpm)'].std()

mean_spo2 = df['Saturasi Oksigen (%)'].mean()
median_spo2 = df['Saturasi Oksigen (%)'].median()
std_spo2 = df['Saturasi Oksigen (%)'].std()

print(f"Rata-rata HR: {mean_hr}, Median HR: {median_hr}, Standar Deviasi HR: {std_hr}")
print(f"Rata-rata SpO2: {mean_spo2}, Median SpO2: {median_spo2}, Standar Deviasi SpO2: {std_spo2}")

Rata-rata HR: 90.6, Median HR: 91.0, Standar Deviasi HR: 11.76813022059532
Rata-rata SpO2: 96.4, Median SpO2: 96.0, Standar Deviasi SpO2: 1.0749676997731399
```

Figure 6. Static Analysis After Eating

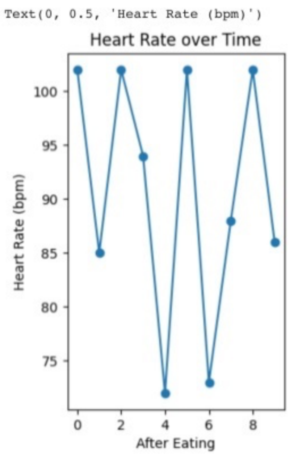


Figure 7. Chart After Eating

From the results of static analysis of heart rate (HR) and oxygen saturation (SpO2) before eating, it was found that the average HR was 90.6 bpm with a median HR of 91.0 bpm. This shows that the heart rate before eating tends to be high but still within the normal range, with a symmetrical data distribution. The HR standard deviation of 11.77 bpm indicates there is a more significant variation in the measured individual heart rates, which could indicate different body responses to certain conditions or stress factors.

For SpO2, the average was 96.4% with a median of 96.0%, indicating that oxygen saturation was within a healthy and stable range. The low SpO2 standard deviation of 1.07% indicates that oxygen saturation values are very consistent with insignificant variation between measurements.

In conclusion, although the heart rate tends to be higher with significant variations, oxygen saturation remains stable and healthy. This shows that although there are some fluctuations in heart rate, the body's oxygenation before eating is in good condition. It is important to continue to monitor HR and SpO2 periodically to ensure these values remain within the normal range, and consultation with a medical professional may be necessary if significant changes occur or if the heart rate is persistently high.

These results show that the HROS-IoT system can provide reliable measurements of heart rate and oxygen saturation under various conditions. However, slight differences in heart rate measurement results after meals may indicate that the HROS-IoT system is more sensitive to physiological changes that occur after food consumption. This sensitivity can be an advantage in the context of more dynamic health monitoring, where slight changes in important parameters need to be carefully noted. Additionally, the low average error in oxygen saturation measurements suggests that HROS-IoT can be an effective and accurate tool for monitoring daily health, providing a viable alternative to commercial devices such as the LK87 oximeter.

E. Discussion

The system will deliver heart rate and saturation oxygen from sensor data to a mobile phone via a Wi-Fi signal from the microcontroller. Figure 8. illustrates how the findings will be displayed in the Blynk program.

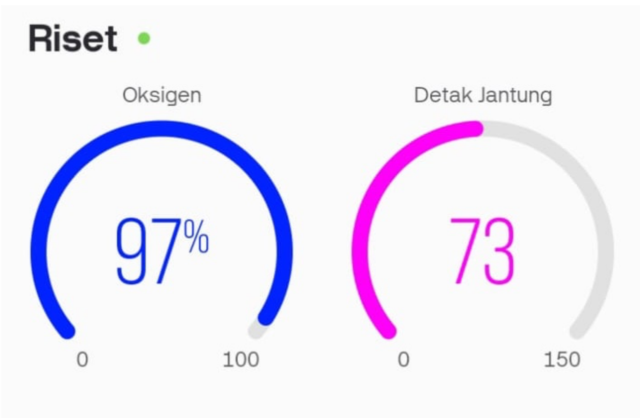


Figure 8. Result on Blynk

Illustrates the heart rate and oxygen saturation results obtained from the processed data of the MAX30102 sensor by the ESP32 microcontroller. This data is transmitted to Blynk via the internet network using Wi-Fi or a cellular hotspot connected to the ESP32. As a result, the heart rate and oxygen levels can be monitored on a smartphone through the Blynk application. The data is displayed in the form of gauges and numerical values. Heart rate measurements range from 0 to 150 BPM, while oxygen saturation measurements range from 0 to 100%.

Apart from providing easy access and real-time monitoring, using the Blynk application also allows users to see trends and patterns in their health data over time. Users can store and analyze historical data, providing deeper insight into their health conditions. With the ability to customize the Blynk application interface, users can add additional features such as alert notifications when heart rate or oxygen saturation values exceed normal limits. This increases safety aspects and responsiveness to sudden changes in health conditions. The implementation of this system shows how IoT technology can be integrated into everyday health monitoring practices, providing a more sophisticated and personalized tool for health management.

F. Conclusion

The HROS-IoT system, which uses the MAX30102 sensor and ESP32 microcontroller, has proven useful in continually monitoring important health indicators like as heart rate and blood oxygen saturation in real time. This technology configuration represents a significant leap in healthcare by allowing quick access to important health data via the Blynk program, which is available remotely via WiFi or cellular connections. This capacity considerably improves healthcare personnel' ability to proactively monitor patients' conditions, especially in emergency-prone contexts such as hospitals.

While the HROS-IoT system produces findings that are generally consistent with commercial measurement devices such as the LK87 oximeter, there are some notable differences in certain conditions. For example, post-meal measurements show somewhat greater heart rate and oxygen saturation levels compared to the LK87, which could be influenced by individual physiological variances, sensor features, and environmental conditions during data collection. Despite these variations, the system's ability to provide comparable data demonstrates its dependability for routine health monitoring and early detection of serious problems.

The HROS-IoT system, which integrates the MAX30102 sensor and ESP32 microcontroller, has tremendous promise for improving real-time patient health monitoring. Testing the system against the LK87 oximeter on different people indicated only minor discrepancies in heart rate and oxygen saturation measurements, with average errors of 5.2 BPM and 1% before meals and 11.3 BPM and 1% after meals. Despite these variations, the HROS-IoT system constantly delivers reliable data, which is vital for early medical treatments, particularly in critical situations such as cardiac arrest in hospitals. Its ability to transmit data remotely via the Blynk application increases medical responsiveness and allows for more effective monitoring. Moving forward, refining IoT technology will be critical to better accuracy, validation, and greater integration into healthcare settings, maximizing patient outcomes and safety overall.

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