HOT Watch: IoT-Based Wearable Health Monitoring System

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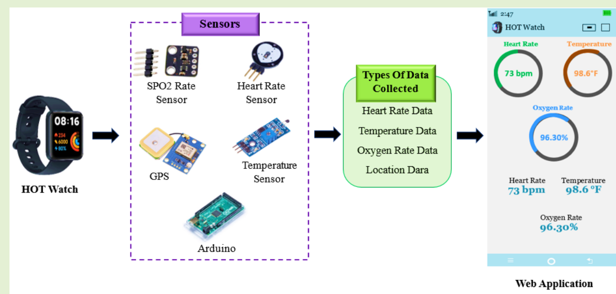
***Abstract*—The Internet of Things (IoT) and wearables involve small embedded devices with sensors collecting data from their surroundings. Nowadays, people have added complexity as well as busyness to their lives and they do not give their health much thought due to their hectic routines. Current health monitoring systems are often cumbersome and inconvenient for patients, leading to poor adherence and delayed detection of health issues. To address this problem, heart rate oxygen rate temperature watch (HOT Watch) an IoT-based wearable health monitoring device has been proposed to track the user's health condition and notify the person with their health details. The HOT Watch employs sensors, such as the MLX90614 temperature sensor, AD8232 electrocardiogram (ECG) sensor, and MAX30100 oximeter sensor to gather health metrics from users. The HOT Watch employs Arduino technology and Bluetooth connectivity to transmit data to a mobile application and the Pan–Tompkins algorithm (PTA) precisely determines the user's heart rate. The proposed method displays the essential health information and alerts users about their health status, including the location data obtained from the GPS sensor in the watch. By continuously tracking vital signs such as temperature, oxygen saturation, and heart rate, individuals can gain valuable insights into their overall health status. These real-time data allow users to monitor their well-being proactively and make informed decisions about their lifestyle and activities. The accuracy of the proposed HOT Watch is 1.40%, 0.70%, and 2.47% higher than the existing Sensor Patch, IoT-based wearable sensor (WS-IoT), and Neo Wear, respectively.**

***Index Terms*—Health monitoring, heart rate oxygen rate temperature watch (HOT Watch), Internet of Things (IoTs), sensors, wearable devices.**



I. Introduction

THE Internet of Things (IoT) is a quickly expanding field that has many uses in a variety of industries, such as sports, fashion, and healthcare [1]. IoT technology has facilitated the development of creative solutions that provide continuous, live health tracking and deliver insightful information to patients and healthcare providers alike [2], [3]. Medical technology has advanced to the point that most of the health factors, such as body temperature, respiratory rate, blood pressure, SpO2, electrocardiogram (ECG), heart rate [4], and blood sugar, may now be monitored with electronic devices that have precise sensors [5].

Advancements in communication technology, especially the internet, have made it possible to remotely track these indicators, which enables the IoT healthcare monitoring. Basic vital signs, such as body temperature, oxygen saturation, and heart rate, are essential for the diagnosis, treatment, and management of a wide range of medical problems [6]. Efficient and precise assessments of these indicators are essential for averting difficulties, evaluating health, and customizing treatment plans [7].

Stress and mental state may be reflected in heart rate. By keeping an eye on heart rate, people might potentially lower their chance of developing health issues linked to stress by identifying times when they are under a lot of stress and managing it [8]. The body's natural reaction to infections, such as bacterial or viral disorders, is elevated body temperature,

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which is frequently shown as fever [9]. It is possible to detect illnesses early and treat them promptly by keeping an eye on variations in body temperature [10]. One basic vital indicator that provides important details about lung function and general health is respiratory rate [11], [12].

Wearables must have wireless connectivity, and Bluetooth low energy (BLE) is frequently used to transfer data [13]. There are a variety of microcontrollers available for use in IoT applications. The decision is based on the particular needs and guidelines [14]. The Arduino is one of the most cutting-edge and well-liked microcontrollers utilized nowadays to connect the automation system to a remote-controlled device [15]. There is an urgent need for an inventive solution that can offer people remote, real-time health monitoring as the world's healthcare difficulties continue to rise [16], [17]. Current health monitoring systems are often cumbersome and inconvenient for patients, leading to poor adherence and delayed detection of health issues. While various wearable health monitoring systems have been explored in recent years, They suffer from many drawbacks such as high cost, limited precision, and complex setup. Some existing systems entail expensive sensor patch development and implementation, while others lack efficiency and accuracy in monitoring health parameters. Moreover, issues related to setup complexity and maintenance further hinder the widespread adoption of existing solutions. To address this problem, a novel heart rate oxygen rate temperature watch (HOT Watch) has been proposed to provide a seamless and user-friendly solution to track health details. The following are the primary contributions of the work.

1) Initially, sensors, such as MLX90614 temperature sensor, AD8232 ECG sensor, and MAX30100 oximeter sensor, are equipped in the HOT Watch that collects health details such as ECG, body temperature, and oxygen rate from the user of the HOT Watch.
2) Then, using Arduino with Bluetooth connectivity, the collected sensor data are given to the mobile application, and the ECG data from the AD8232 ECG sensor are given as input to the Pan–Tompkins algorithm (PTA) to calculate the heart rate of the HOT Watch's user accurately.
3) Finally, all the data are given to the mobile application, which shows the heartbeat rate, body temperature, and oxygen rate, and it notifies the user that their health condition is normal or abnormal with the location of the user using the GPS sensor equipped in the HOT Watch.

The proposed system aims to bridge the gap in existing health monitoring solutions by offering a seamless and user-friendly approach to continuous health tracking. It not only addresses the limitations of current systems but also empowers individuals to take control of their well-being through proactive monitoring.

The remainder of this study is explained in the way that follows. Section II analyzes the study based on the literature. Section III offers a thorough description of the proposed system. Section IV represents the result and discussion, and Section V represents the conclusion.

II. Literature Survey

In the last few years, several studies have used wearable technology to monitor health. A number of contemporary evaluation techniques are discussed in the part that follows, along with some of their drawbacks.

Wu et al. [18] suggested a wearable sensor patch that is small, light, and low power for use in IoT-connected healthcare applications. The experiments' outcomes demonstrate how well the developed sensor patch performs when compared to a commercially available reference medical device. A limitation is that wearable sensor patch development and implementation might be costly. Huifeng et al. [19] presented the IoT-based wearable sensors (WS-IoT) for sportspeople's ongoing health monitoring system. Use wearable tracking devices to monitor activity records and get health information. Machine learning algorithms with effective optimization are provided to examine and monitor the health of athletes. The efficiency of the developed system is assessed through conversation and experimental findings.

Al Bassam et al. [20] developed a wearable monitoring system based on the IoT to measure different COVID-19-linked vital indicators. The design functions as a crucial platform that establishes the restrained symptom readings for analysis, management, and monitoring. The work also describes the use of a wearable digital remote platform as a monitoring tool to track the recovery and health of patients.

Cay et al. [21] designed the "NeoWear," a smart textile chest band with IoT connectivity, to track respiratory rates and identify infant apnea episodes. The initial findings are encouraging in that they demonstrate how well NeoWear works. The results indicate that the accuracy in detecting apnea on the infant mannequin was almost 97%.

Qiu et al. [22] suggested the IoT-based hierarchical health monitoring model (IoT-HHMM) to accomplish an efficient evaluation of wearable health monitoring devices for athletes. The results show that the proposed IoT-HHMM achieves a high accuracy ratio of 98.4% when compared to conventional approaches. Nwibor et al. [23] presented the creation and implementation of an IoT-based remote health monitoring system that analyzes blood pressure, blood oxygen saturation levels, and heart rate. The BP, HR, and SpO2 of each user were estimated using the measured PPG signal. To find the PPG signal's greatest peak, an AMBP detection technique was created.

Mohammadian et al. [24] suggested a wearable light sensor node that can be used with the IoTs to monitor EDI exposure in practical situations. Their device has a 30-s sample cycle and lasts for 3.5 days between charges. With ten measurement channels spanning 415–910 nm, it strikes a balance between accuracy and affordability. The results show that it is possible to achieve accurate light sensing, even at wrist-worn locations. Mai et al. [25] presented the Ear-EEG emotion recognition (EEER) system, which integrates IoT capabilities and uses a deep neural network for improving human emotion detection, processing, interpretation, and emulation. According to experimental results, the trained ViT model with SPT and LSA achieves an average accuracy of 92.39% on untrained datasets, outperforming recent models in this regard.

TABLE I
COMPARISON OF EXISTING TECHNIQUE WITH PROPOSED SYSTEM

AUTHORS	METHODS	ADVANTAGES	DISADVANTAGES
T. Wu, et al. [18]	wearable sensor patch for healthcare	low-power sensor patch	Costly development and implementation
Huifeng, W., et al., [19]	WS-IoT	Continuous monitoring for athletes.	privacy concerns, data security risks, and costs are high
Al Bassam, N., et al., [20]	wearable monitoring system	Enables remote monitoring	Connectivity issues, limit accessibility
Cay, G., et al. [21]	"NeoWear," a smart textile chest band	Average error in measuring respiration rate	Potential limitations in real-world infant use and high-cost
Qiu, Y., et al., [22]	IoT-HHMM	Reduces energy usage,	High complexity in implementation and maintenance
C. Nwibor et al., [23]	IoT-based remote health monitoring system	Provides measurement of multiple vital signs	Restricted validity and accuracy of sensor readings.
Mohammadian, N., et al., [24]	A wearable light sensor node	feasibility of accurate light sensing	Limited battery life
Mai, N.D., et al., [25]	Ear-EEG Emotion Recognition (EEER) system	achieving high accuracy on untrained datasets	challenges in implementation and scalability.
Proposed	HOT Watch	Seamless connectivity to mobile app, Low Cost	Potential limitations in certain contexts or user populations

While existing literature explores various aspects of wearable technology for health monitoring, there remains a gap in addressing the overall efficiency, cost-effectiveness, simplicity of setup and maintenance, and precision of these systems. Table I represents the comparison of the existing technique with the proposed technique with advantages and disadvantages. Moreover, there is a need for a comprehensive solution that integrates these disparate functionalities into a single platform. The proposed HOT Watch aims to bridge this gap by offering a unified solution to overcome the limitations of existing approaches.

The HOT Watch fills gaps in existing research by combining wearable sensors and IoT tech for real-time health monitoring. Unlike past studies with cost and precision issues, it uses advanced sensors such as MLX90614, AD8232, and MAX30100, along with Bluetooth, for accurate data collection and mobile transmission. This innovation promises efficient remote health monitoring, improving upon current systems.

III. HOT WATCH

In this section, a novel HOT Watch an IoT-based wearable health monitoring system has been proposed to track the user's health condition and notify the person of their health details. Initially, sensors, such as MLX90614 temperature sensor, AD8232 ECG sensor, and MAX30100 oximeter sensor, are equipped in the HOT Watch that collects health details such as ECG, body temperature, and oxygen rate from the user of the HOT Watch. Then, using Arduino with Bluetooth connectivity, the collected sensor data are given to the mobile application, and the ECG data from the AD8232 ECG sensor are given as input to the PTA to calculate the heart rate of the HOT Watch's user accurately. Finally, all the data are given to the mobile application, which displays the heartbeat rate, body temperature, and oxygen rate, and it notifies the user that their health condition is normal or abnormal with the location of the user using the GPS sensor equipped in the HOT Watch. Fig. 1 illustrates the entire workflow of the proposed HOT Watch.

The study was designed to address the limitations of current health monitoring systems by proposing a novel HOT Watch. The design involved integrating sensors such as the MLX90614 temperature sensor, AD8232 ECG sensor, and MAX30100 oximeter sensor into a wearable device. The device collects vital health data such as ECG, body temperature, and oxygen rate from users. In addition, the study employed Arduino with Bluetooth connectivity to hand over the collected sensor data to a mobile app for further analysis and display. PTA was utilized to accurately calculate the user's heart rate.

A. Sensing Unit

Users wear a smartwatch equipped with various sensors with Bluetooth connectivity. Factors, such as body temperature, heart beat rate, and blood oxygen level, are collected from the human body by the sensors that are embedded in the HOT Watch. The HOT Watch uses the MLX90614 temperature sensor for temperature measurement. The MAX30100 oximeter sensor monitors oxygen saturation levels.

Fig. 2 shows the sensors that are integrated into the HOT Watch. The HOT Watch also features the AD8232 ECG sensor for precise heart rate measurement. The GPS sensor determines the user's precise location using signals from Earth-orbiting satellites.

Data transmission from sensors to the mobile application is facilitated by the Arduino ESP8266, an open-source microcontroller with Wi-Fi and Bluetooth capabilities, ensuring compatibility and efficient processing for IoT applications.

B. Data Processing

ECG data from the AD8232 ECG sensor are given to the PTA to calculate the heart rate of the HOT Watch's user accurately.

1) Pan–Tompkins Algorithm: One popular method for identifying QRS complexes in ECG data is the PTA. The R-peaks, or the highest points of the QRS complex, can be found in the ECG signal with the aid of this technique. With the help of these points, the heartbeat rate can be calculated easily. The architecture of PTA is shown in Fig. 3.

The initial stage of the PTA involves filtering the raw ECG data to emphasize the QRS complex. A bandpass filter is commonly utilized for this purpose, as it eliminates low-frequency elements and noise while preserving the QRS frequency range. The following equation represents the filtered signal:

$$F = Y[m] \tag{1}$$

where $Y[m]$ represents the filtered ECG signal at discrete sample index m. One way to depict the differential is as

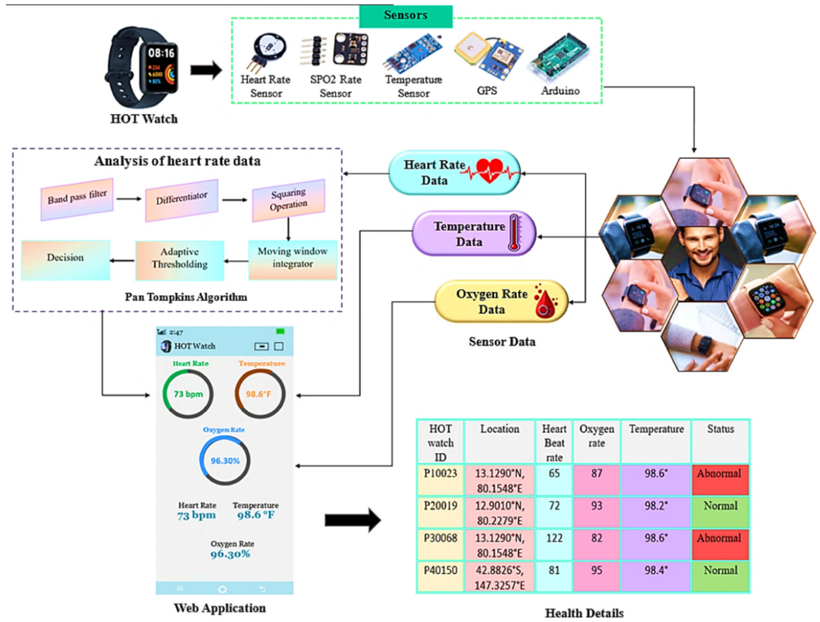

Fig. 1. Proposed workflow of HOT Watch.

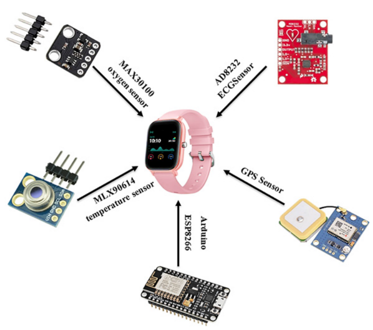

Fig. 2. Sensors integrated in HOT Watch.

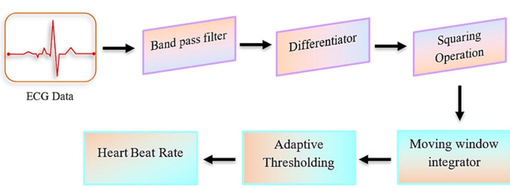

Fig. 3. Architecture of PTA.

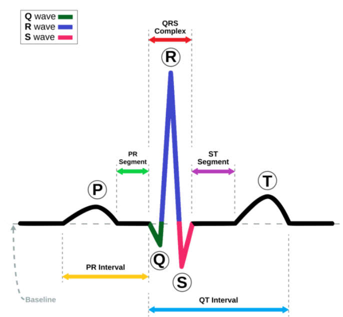

Fig. 4. ECG beat.

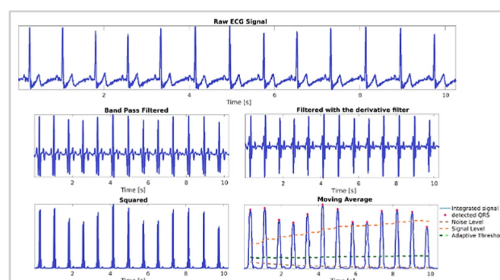

Fig. 5. Process of Pan–Tompkins algorithm.

follows:

$$X[m] = Y[m] - Y[m-1] \tag{2}$$

where $X[m]$ indicates the signal that is distinguished at the discrete sample index m. The signal samples are squared point by point in this nonlinear transformation, which is given in the following equation:

$$Z[m] = X[m]^2 \tag{3}$$

where $Z[m]$ represents the signal squared at discrete sample index m. Then, integrate the newly defined interval window after summing the area under the squared waveform across a suitable interval. This aids in the identification of QRS complexes which is shown in the following equation:

$$V[m] = \sum_{j=m-P+1}^{m} Z[j] \tag{4}$$

where $V[m]$ denotes the discrete sample index m of the integrated signal and P is the extent of the integration window. Usually, it is resolute by the anticipated duration of the QRS complex. Fig. 4 depicts the diagram for the ECG beat.

To identify QRS complexes, a dynamic threshold is employed. The integrated signal's mean and standard deviation over a given period are frequently used to calculate this threshold. By using this, the heart beat rate is calculated. Pan–Tompkin's processing is shown in Fig. 5.

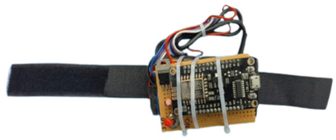

Fig. 6. HOT Watch's hardware model.

The calculated heat beat of the person using PTA and other health details are given to the mobile application by connecting the HOT Watch with the mobile application. The mobile application shows the accurate heart beat rate, body temperature, and oxygen rate, and it notifies the user of their health condition such as normal or abnormal with their location.

The study was carried out through hardware implementation, where key components, such as sensors and microcontrollers, were integrated into the HOT Watch. Real-world scenarios were simulated to demonstrate the usage of the HOT Watch among different users. Experiments were also carried out as part of the study to assess how well the system performed in monitoring critical health indicators such as temperature, heart rate, and oxygen saturation across different age and gender groups. Data analysis was conducted by PTA to calculate heart rates accurately based on ECG data collected from the AD8232 ECG sensor. In addition, the study involved analyzing temperature and oxygen rate data obtained from the MLX90614 temperature sensor and MAX30100 oximeter sensor, respectively. The results were presented graphically, showcasing the tracked health details of different users and evaluating heart rate, oxygen rate, and temperature based on age and gender.

IV. Results and Discussion

In this study, a real-time HOT Watch is developed to track the user's health in both normal and abnormal conditions. This section assesses the feasibility, precision, and efficacy of the suggested HOT Watch through a practical implementation analysis.

A. Hardware Implementation

The HOT Watch hardware execution involves integrating key components, such as the MLX90614 temperature sensor, MAX30100 oximeter sensor, GPS, AD8232 ECG sensor, and Arduino ESP8266.

The hardware model of the HOT Watch is shown in Fig. 6, which also highlights how important components that are necessary for thorough health monitoring have been integrated. The integrated components of the HOT Watch function in concert to provide a comprehensive health monitoring experience by accurately capturing and processing critical health information.

The login page for the mobile application linked to the HOT Watch is shown in Fig. 7. By providing their credentials, users can log in. After completing the authentication process, users can access the application's UI, which provides them with access to all of their health information including real-time monitoring and notifications for administration and evaluation.

Fig. 8 shows several users wearing the HOT Watch in real-world scenarios. This graphic depiction emphasizes how the

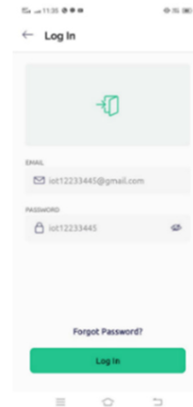

Fig. 7. Login page of the application.

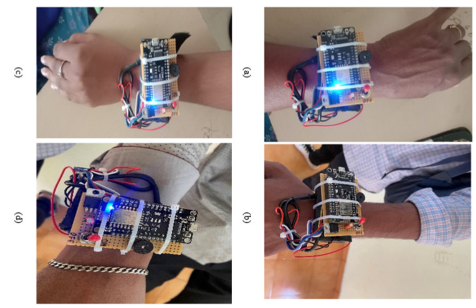

Fig. 8. HOT Watch usage among different users.

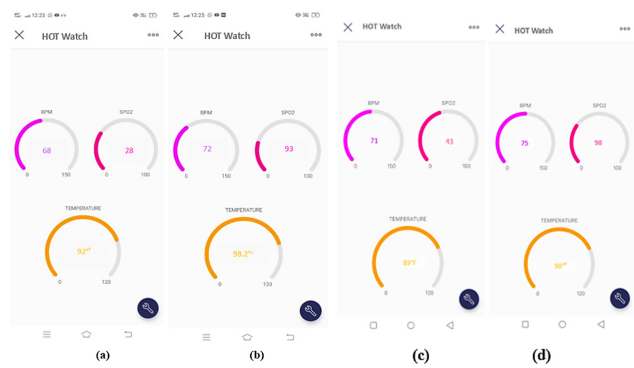

Fig. 9. Tracked health details of different users.

health monitoring system is used in the actual world. The heart rate sensor uses photoplethysmography to notice blood flow changes in the wrist, the temperature sensor gauges skin temperature, and the oxygen rate sensor measures blood oxygen levels using light absorption.

Fig. 9(a)–(d) shows the tracked health details of user a, user b, user c, and user d using the proposed HOT Watch. With these details, user can able to track their health details such as heart beat rate, body temperature, and oxygen rate at any time.

Fig. 10(a)–(d) shows the health status notification of user a, user b, user c, and user d. The notification page shows the health status whether normal or abnormal with the location of the users. The location data are given by the GPS sensor, which is equipped in the HOT Watch.

B. Experimental Result of HOT Watch

The following criteria are used to determine the various results: an analysis based on age and gender.

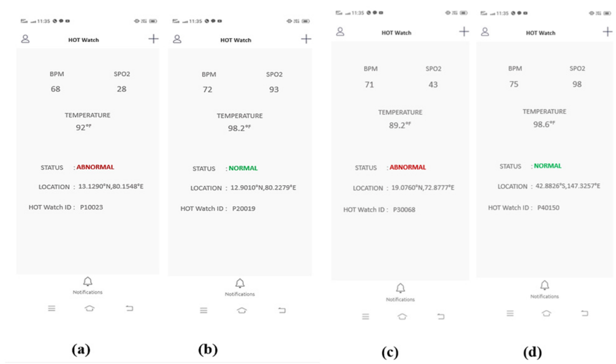

Fig. 10. Notification status of different users.

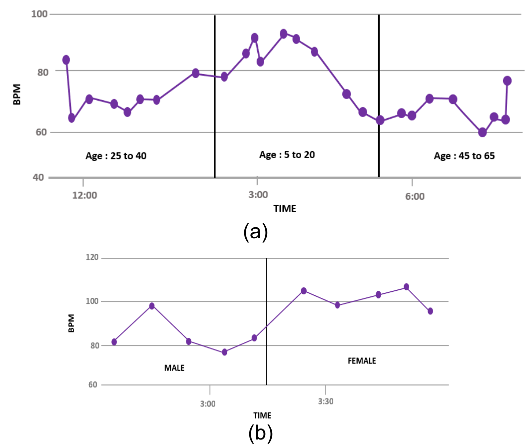

Fig. 11. (a) Depicts heart rates spanning ages 5 to 20 up to 90 bpm, bpm, including normal adult rates at 72 bpm and average rates for adults aged 45 to 65 at 65 bpm. (b) Illustrates that women typically have higher heart rates than men, with peaks on the right and left representing heart rates for individuals of the same age.

1) Age and Gender-Based Evaluation of Heartbeat Rate: Heart rate varies across genders and ages, as seen in the HOT Watch's monitoring of various age groups and genders, pinpointing distinct heart rate patterns.

2) Age and Gender-Based Evaluation of Oxygen Rate: The HOT Watch monitors oxygen saturation and highlights differences across age and gender.

Fig. 12(a) illustrates human oxygen concentration over time across different ages. The graph's right portion represents oxygen levels in the elderly, the middle section depicts levels in young children, and the leftmost part shows levels in adults. Fig. 12(b) examines a similar concept, focusing on gender differences. Females' oxygen rates, shown on the right, tend to be slightly lower than males' oxygen rates, depicted on the left.

3) Age and Gender-Based Evaluation of Temperature: The HOT Watch tracks body temperature, showing differences among ages and proving body temperature that is not influenced by gender.

As people age, body temperature tends to decrease, as shown in Fig. 13(a). This indicates an inverse relationship between age and body temperature. In Fig. 13(b), female and male body temperatures are plotted against time, with females on the right and males on the left.

Fig. 14 presents a comparative analysis of accuracy among four different methods: Sensor Patch [18], WS-IoT [19], Neo

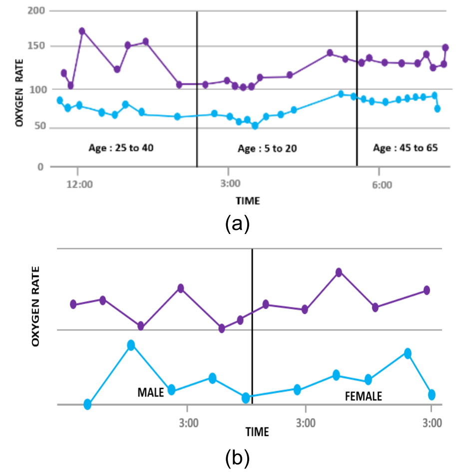

Fig. 12. (a) Readings of people's oxygen rate at various ages. (b) Different genders' readings of human oxygen rates.

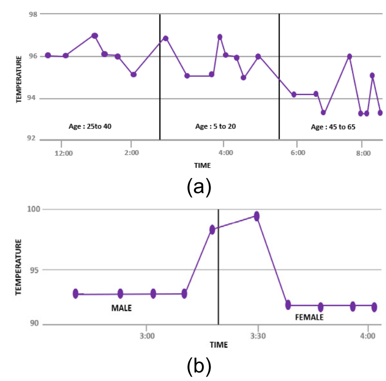

Fig. 13. (a) Observations of the body temperature of people at various ages. (b) Different genders' readings of the human body temperature.

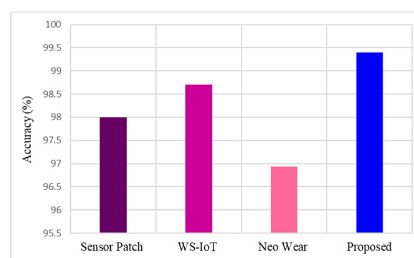

Fig. 14. Comparison in terms of accuracy.

Wear [21], and the proposed HOT Watch. The Sensor Patch method achieves an accuracy of 98%, while the WS-IoT method surpasses it with an accuracy of 98.7%. The NeoWear method lags with an accuracy of around 96.4%. Notably, the proposed HOT Watch demonstrates the highest accuracy, exceeding 99.4%. This comparison indicates the superior performance of the proposed HOT Watch in terms of accuracy, highlighting its potential advantage over existing techniques. The accuracy of the proposed HOT Watch is 1.40%, 0.70%, and 2.47% higher than the existing Sensor Patch, WS-IoT, and Neo Wear, respectively.

V. CONCLUSION

In this article, a novel HOT Watch, an IoT-based wearable health monitoring device, has been proposed to track the user's health condition and notify the person with their health details. The HOT Watch offers a promising solution to the ever-evolving healthcare industry's demand for real-time, distant monitoring of health. By integrating sensors such as the MLX90614 temperature sensor, AD8232 ECG sensor, and MAX30100 oximeter sensor, this innovative device collects vital health data such as ECG, body temperature, and oxygen rate. The system's efficient data processing, including the use of the PTA for heart rate calculation, ensures accurate and timely health information for users. The seamless connectivity to a mobile application further enhances the user experience, providing real-time access to their health metrics and notifying them of their health status. The accuracy of the proposed HOT Watch is 1.40%, 0.70%, and 2.47% higher than those of the existing Sensor Patch, WS-IoT, and Neo Wear, respectively. While the HOT Watch shows promise in addressing current healthcare challenges, it may have limitations in certain contexts or user populations. Future research might focus on creating predictive algorithms to analyze health data patterns, aiding in the early detection of health concerns or opportunities for wellness interventions.

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References

[1] A. M. Rahmani, S. Bayramov, and B. K. Kalejahi, "Internet of Things applications: Opportunities and threats," *Wireless Pers. Commun.*, vol. 122, no. 1, pp. 451–476, Jan. 2022, doi: 10.1007/s11277-021-08907-0.

[2] S. Zeadally and O. Bello, "Harnessing the power of Internet of Things based connectivity to improve healthcare," *Internet Things*, vol. 14, Jun. 2021, Art. no. 100074, doi: 10.1016/j.iot.2019.100074.

[3] G. Sreetha and G. Santhiya, "SAFE-ACID: A novel security assessment framework for IoT intrusion detection via deep learning," *Int. J. Data Sci. Artif. Intell.*, vol. 2, no. 1, pp. 20–26, 2024.

[4] A. Appathurai et al., "A study on ECG signal characterization and practical implementation of some ECG characterization techniques," *Measurement*, vol. 147, Dec. 2019, Art. no. 106384, doi: 10.1016/j.measurement.2019.02.040.

[5] C. Virginia Anikwe et al., "Mobile and wearable sensors for data-driven health monitoring system: State-of-the-art and future prospect," *Expert Syst. Appl.*, vol. 202, Sep. 2022, Art. no. 117362, doi: 10.1016/j.eswa.2022.117362.

[6] M. Erol, F. Ulengin, and H. A. Dinçer, "A novel triage system design," in *Proc. Int. Congr. Hum.-Comput. Interact., Optim. Robot. Appl. (HORA)*, Jun. 2022, pp. 1–7, doi: 10.1109/hora55278.2022.9799950.

[7] S. Singh, D. K. Sarma, V. Verma, R. Nagpal, and M. Kumar, "Unveiling the future of metabolic medicine: Omics technologies driving personalized solutions for precision treatment of metabolic disorders," *Biochem. Biophys. Res. Commun.*, vol. 682, pp. 1–20, Nov. 2023, doi: 10.1016/j.bbrc.2023.09.064.

[8] S. Li, Y. Wang, and Y. Z. Rasmussen, "Studying interpreters' stress in crisis communication: Evidence from multimodal technology of eye-tracking, heart rate and galvanic skin response," *Translator*, vol. 28, no. 4, pp. 468–488, Oct. 2022, doi: 10.1080/13556509.2022.2159782.

[9] Y. Li, "Bacterial infection," in *Radiology of Infectious and Inflammatory Diseases—Volume 3: Heart and Chest*, vol. 3, 2023, pp. 33–60.

[10] D. M. Alshehri, "Blockchain-assisted Internet of Things framework in smart livestock farming," *Internet Things*, vol. 22, Jul. 2023, Art. no. 100739, doi: 10.1016/j.iot.2023.100739.

[11] S. Zafar, N. Iftekhar, A. Yadav, A. Ahilan, S. N. Kumar, and A. Jeyam, "An IoT method for telemedicine: Lossless medical image compression using local adaptive blocks," *IEEE Sensors J.*, vol. 22, no. 15, pp. 15345–15352, Aug. 2022.

[12] K. P. Joshua and A. J. Prabhu, "Efficient data search and retrieval in cloud assisted IoT environment," *Int. J. Data Sci. Artif. Intell.*, vol. 2, no. 1, pp. 1–6, 2024.

[13] A. Barua, M. A. Al Alamin, Md. S. Hossain, and E. Hossain, "Security and privacy threats for Bluetooth low energy in IoT and wearable devices: A comprehensive survey," *IEEE Open J. Commun. Soc.*, vol. 3, pp. 251–281, 2022, doi: 10.1109/OJCOMS.2022.3149732.

[14] M. R. Rashel et al., "Internet of Things platform for advantageous renewable energy generation," in *Proc. Int. Conf. Adv. Comput. Appl.*, 2022, pp. 107–117, doi: 10.1007/978-981-16-5207-3_10.

[15] A. Kumar Pandey and W. Patel, "A smart vehicle control remotely using WiFi," in *Proc. 11th Int. Conf. Syst. Modeling Adv. Res. Trends (SMART)*, Dec. 2022, pp. 1185–1191, doi: 10.1109/SMART55829.2022.10047780.

[16] A. V. L. N. Sujith, G. S. Sajja, V. Mahalakshmi, S. Nuhmani, and B. Prasanalakshmi, "Systematic review of smart health monitoring using deep learning and artificial intelligence," *Neurosci. Informat.*, vol. 2, no. 3, Sep. 2022, Art. no. 100028, doi: 10.1016/j.neuri.2021.100028.

[17] R. Sundarasekar and A. Appathurai, "Automatic brain tumor detection and classification based on IoT and machine learning techniques," *Fluctuation Noise Lett.*, vol. 21, no. 3, Jun. 2022, Art. no. 2250030.

[18] T. Wu, F. Wu, C. Qiu, J.-M. Redouté, and M. R. Yuce, "A rigid-flex wearable health monitoring sensor patch for IoT-connected healthcare applications," *IEEE Internet Things J.*, vol. 7, no. 8, pp. 6932–6945, Aug. 2020, doi: 10.1109/JIOT.2020.2977164.

[19] W. Huifeng, S. N. Kadry, and E. D. Raj, "Continuous health monitoring of sportsperson using IoT devices based wearable technology," *Comput. Commun.*, vol. 160, pp. 588–595, Jul. 2020, doi: 10.1016/j.comcom.2020.04.025.

[20] N. Al Bassam, S. A. Hussain, A. Al Qaraghuli, J. Khan, E. P. Sumesh, and V. Lavanya, "IoT based wearable device to monitor the signs of quarantined remote patients of COVID-19," *Informat. Med. Unlocked*, vol. 24, Jan. 2021, Art. no. 100588, doi: 10.1016/j.imu.2021.100588.

[21] G. Cay et al., "NeoWear: An IoT-connected e-textile wearable for neonatal medical monitoring," *Pervasive Mobile Comput.*, vol. 86, Oct. 2022, Art. no. 101679, doi: 10.1016/j.pmcj.2022.101679.

[22] Y. Qiu, G. Liu, B. A. Muthu, and C. B. Sivaparthipan, "Design of an energy-efficient IoT device with optimized data management in sports person health monitoring application," *Trans. Emerg. Telecommun. Technol.*, vol. 33, no. 10, Oct. 2022, Art. no. e4258, doi: 10.1002/ett.4258.

[23] C. Nwibor et al., "Remote health monitoring system for the estimation of blood pressure, heart rate, and blood oxygen saturation level," *IEEE Sensors J.*, vol. 23, no. 5, pp. 5401–5411, Mar. 2023, doi: 10.1109/JSEN.2023.3235977.

[24] N. Mohammadian et al., "A Wrist–Worn Internet of Things sensor node for wearable equivalent daylight illuminance monitoring," *IEEE Internet Things J.*, vol. 11, no. 9, pp. 16148–16157, May 2024.

[25] N.-D. Mai, H.-T. Nguyen, and W.-Y. Chung, "Deep learning-based wearable ear-EEG emotion recognition system with superlets-based signal-to-image conversion framework," *IEEE Sensors J.*, vol. 24, no. 7, pp. 11946–11958, Apr. 2024.

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