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OXY SENSE-WEAR: A REAL-TIME IOT-BASED WEARABLE PLATFORM FOR CONTINUOUS MULTI-PARAMETER HEALTH MONITORING

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SUMMARY

Purpose- The main objective of the proposed paper is to create and implement a real-time wearable health monitoring system based on IoT, i.e., Oxy Sense-Wear, that will enable the constant control of the main physiological parameters, such as ECG, EMG, SpO2, body temperature, and physical activity. The system is aimed at long-term surveillance of the elderly, bedridden, and long-term chronic disease patients, and this allows the patient to identify abnormal health conditions in time and provide proper medical care. Design/methodology/approach-The given device is a soft wearable chest strap with built-in biomedical sensors and powered by an ESP32 microcontroller. Live information is collected, analyzed, and sent through Wi-Fi to a cloud-based server and Android smartphone application. Physiological alerts will activate the buzzer and instant mobile notification when the physiological thresholds are surpassed. The software was used to design and simulate the hardware that was being developed with Proteus and create firmware in the Arduino IDE and the mobile application on Android Studio. Findings- There is a reliable real-time performance as experimental assessment shows heart rate changes with a deviation of +/-2 BPM, SpO 2 values were always in the range of 96-98, and body temperature was monitored accurately between 36.0 o C and 38.8 o C. Fall events were identified with great success at acceleration levels more than 2.5 g, and low false positives. The system recorded a mean alert latency of less than 500 ms and could operate continuously (8 to 12 hours, depending on charge) and thus proved to be viable in the case of personal and clinical remote healthcare monitoring. Originality/value-The proposed Oxy Sense-Wear platform is the first to offer a single multi-parameter sensing, real-time alerting, cloud synchronization, mobile connectivity, and OTA-enhanced platform in a small and wearable size. The work done in the future will be on the implementation of more sophisticated machine-learning algorithms for predictive health analytics, improving the security of the collected data by using encrypted authentication to provide more connection options with the use of the BLE and 5G technology to support the large-scale implementation and integration with the hospital information system. In an effort to be more concise and clearer, this manuscript lays emphasis on system-level insights, comparative appraisal, and quantitative performance assessment rather than a description of the components at a much more detailed level.

Key words: *IoT-based health monitoring, wearable technology, real-time alerts, cloud analytics, remote healthcare, patient safety.*

INTRODUCTION

Over the last few years, the need for continuous real-time monitoring of one's health has grown with the rise of chronic diseases, aging populations, and the need for efficient home care. Traditional patient monitoring systems, though efficient within medical establishments, are typically cumbersome, costly, and incapable of providing real-time feedback outside of healthcare facilities. These limitations are significant risks, particularly for patients with cardiovascular diseases, neurological disease patients, or mobility-impaired patients such as stroke patients or bedridden patients. Delay in detecting abnormal physiological conditions can lead to delayed treatment, resulting in severe complications or even fatalities.

The advent of wearable technology and the Internet of Things (IoT) revolutionized personal healthcare. Wearable devices incorporated

With IoT, it can provide unobtrusive, long-term monitoring of health, along with the comfort of mobility, cost-effectiveness, and improved patient comfort. Biomedical sensors are embedded in wearable devices that offer a platform for the acquisition of physiological information in real time, remote processing, and the generation of alarms on the detection of abnormal conditions. However, the scope of most wearables being made available in the market is currently narrowly limited. They usually monitor just one or two parameters, do not integrate with cloud platforms, or are dependent on proprietary technologies, which do not allow scalability and flexibility.

To address these limitations, the system proposed here, Oxy Sense-Wear, appears in the shape of a smart, multi-sensor chest belt that incorporates fundamental biomedical sensors for continuous measurement of key health parameters (Yan et al) [7]. The device combines ECG, EMG, SpO2, temperature, and motion sensors (gyroscope and accelerometer) in a compact and slick design and integrates them. With the help of an ESP32 controller chip, the device allows for data collection and wireless transmission into the cloud service and app in real time. With that, practitioners and clinicians directly receive real-time updated data for all patients and respond very quickly whenever unusual patterns appear.

Among the strongest features of Oxy Sense-Wear is that it takes an integrated approach to health monitoring. By combining multiple sensors into a small, wear-friendly unit, the device gives a comprehensive view of the patient's health. The ECG sensor provides an overview of the electrical function of the heart and detects arrhythmias and other cardiovascular irregularities. The EMG sensor measures muscle activity, particularly useful for the rehabilitation of stroke or detecting neuromuscular illness. The SpO2 sensor estimates the concentration of oxygen in blood using photoplethysmography and helps in detecting respiratory illness. The temperature sensing detects infection or inflammatory processes, and the accelerator and the gyro sensor help in detecting falls and postures, which are critically important in geriatric and vulnerable patients. A combination of these sensors with an IoT-based microcontroller, such as the ESP32, allows one to achieve strong communication and real-time notification. The ESP32 facilitates the gathering and processing of data and transmission of the wireless data through Wi-Fi to an Android mobile application and cloud storage. The interconnectedness provides full-time remote follow-up even in remote or resource-limited regions and decreases the reliance on hospital visits. System-generated alarms are sent instantaneously via mobile apps and buzzer alarms locally, enabling instant caregiver or healthcare provider intervention. Miladh ans Wei., The inspiration behind the development of Oxy Sense-Wear lies in the pressing need for a scalable, low-cost, and effective remote monitoring solution [1]. Especially in the wake of global health pandemics such as the COVID-19 pandemic, the demand for remote healthcare solutions is clear. The system is designed to provide not just monitoring but also early anomaly detection, facilitating proactive healthcare management.

Oxy Sense-Wear can save several lives of patients as well as decrease the load on the healthcare system by decreasing the time lag between the emergence of the symptom and the arrival of the medics. The device has polymer-based flexible materials to encase sensor modules in regard to user comfort and the wearability of the device in the long term. The band of the chest is designed in an ergonomic form so as to be non-invasive, and it is highly ventilated to avoid the inconvenience of suffering during prolonged time in clothes. This ensures that the device is comfortable to wear by several classes of users, including aged people, physiotherapy patients, and patients with long-term illnesses who need constant monitoring. The system is also energy efficient by use of a rechargeable lithium-ion battery, which is operated using an onboard voltage regulator. The fact that the sensors and microcontrollers use low power means that they will last longer on their battery, and that the system can be left to run without much recharging of the battery.

The energy-efficient nature of the system increases its usability in practical applications, especially in areas where easy access to charging stations may not be available.

From the standpoint of circuit design, the system uses conventional but reliable circuit elements that enable sensor stability, signal purity, and system dependability. Filtering and conditioning of analog and digital sensor signals are done, and then interpreted by the ESP32. This is to guarantee good data acquisition at a low noise level, which is a requirement in biomedical applications.

Oxy Sense-Wear has the real-time monitoring capability, which is complemented by the capability to store as well as analyze historical information. This attribute is especially useful in monitoring the progression of chronic conditions or improvements in the course of rehabilitation over extended periods of time. Healthcare professionals can see trends and patterns in the patient's physiological readings, allowing evidence-based decision-making and customized treatment protocols.

Contributions

The paper presents a proposal for a new real-time IoT-enabled wearable device, Oxy Sense-Wear, which can simultaneously measure various physiological parameters: ECG, EMG, SpO 2, body temperature, and physical activity in a single, lightweight, and non-invasive chest-worn device, and thus break the constraints of single-parameter wearable devices currently used.

It presents a low-latency IoT architecture with on-device anomaly detection and dual-mode alerting, which can achieve a response time of less than 500 ms with local buzzer alerts and cloud-connected mobile notifications, to increase patient and medical responsiveness in real-time.

The paper has shown an energy-efficient and scalable wearable system that can support up to 812 hours of continuous functionality, cloud synchronization, over-the-air updates, and modular sensor configuration, therefore, rendering the system applicable in long-term usage in a home-based and clinical healthcare environment.

Paper Organization: There are the following sections of the paper: Section 1: Introduction presents the need for continuous multi-parameter health monitoring and limitations of existing wearable systems. Section 2 is the background and literature review, which will cover the recent developments in wearable health monitoring and how Oxy Sense-Wear fills the gaps. Section 3 is a description of the system architecture, which includes sensor modules, data collection, wireless transmission, and user interface. Section 4 describes the hardware design, which comprises biomedical sensors, microcontroller integration, and power management. The software infrastructure and the communication protocols are described in Section 5 and include the firmware, data acquisition, anomaly detection, and cloud/mobile connection. Section 6 deals with signal processing and mathematical modeling of ECG, EMG, SpO 2, temperature, and motion signals. Section 7 contains experimental setup, performance evaluation, and results of latency, accuracy, and energy efficiency. Section 8 explains geriatric care, hospital, home monitoring, and research applications and uses. Lastly, the last section of the paper is the conclusion that gives the significant findings, limitations, and future research directions.

BACKGROUND AND LITERATURE REVIEW

Wearable health monitoring systems have developed at a very fast pace in the past few years through the convergence of embedded systems, biomedical sensors, and Internet of Things (IoT) technologies. Greater availability of non-invasive miniature devices has facilitated continuous monitoring of patients, particularly in ambulatory situations. However, even with greater interest and numerous commercial offerings, present wearable systems continue to face issues of sensor integration, real-time processing, data accuracy, and power efficiency.

The demand for constant and real-time monitoring is particularly strong in inpatient groups such as stroke, elderly, and chronic cardiovascular or neuromuscular disease patients. Traditional monitoring devices, which are typically placed in hospitals, tend to be large and very expensive, with poor adaptability for homecare or ambulatory patients. Chandrasekaran et al. emphasize that, despite the fact that wearable devices have made healthcare data more accessible to patients, there still exist issues with privacy and data security, as well as incorporating devices into more medical systems [2]. The early wearable systems were largely confined to systems that monitored only one parameter at a time- e.g., activity or heart rate - providing very minimal information about the general physiology of a patient. For instance, commercial fitness bands typically monitor uncomplicated parameters such as pulse or steps but fail to provide medically relevant metrics such as ECG traces or oxygen saturation. Moreover, most of these platforms are not interconnected, are not cloud-based, and do not support good real-time alerting.

Das et al [3] stress that the interpretation of biomedical signals like ECG, EMG, and EEG is important for the diagnosis of many disorders. However, their recording and processing are usually confined to stationary, dedicated equipment, which is unsuitable for round-the-clock, home-based monitoring. Akkaya's work promotes lightweight, real-time signal acquisition and noise reduction in wearable forms, which is a problem Oxy Sense-Wear targets directly [14].

Several recent developments have attempted to bridge this gap by proposing multi-sensor systems with wireless data communication. Caixeiro et al. [4] outline the application of wearable systems in remote healthcare monitoring and highlight the need for accurate data acquisition and real-time processing to enable effective diagnostics and treatment. However, problems such as limited battery life, inadequate calibration, and non-standardized communication protocols still plague most implementations.

Canali et al. further lists these limitations through the identification of interoperability problems in the data, and issues with fairness and health equity [5]. They consider that most wearable systems adopt a "one-size-fits-all" approach, which detracts from effectiveness for the variety of patients. Wearables also need to function in heterogeneous environments and be able to accommodate integration into multiple medical databases and systems. Oxy Sense-Wear architecture addresses these recommendations by offering seamless IoT integration and a flexible, expandable platform for patient monitoring.

Debnath et al. [6] describe an IoT-oriented real-time health monitoring system that collects sensor data and wirelessly transfers it to healthcare staff. While the system supports rudimentary functionality such as data aggregation and alert triggering, it does not address physical form factor constraints, long-term wearability, or multi-sensor fusion—gaps that are well covered by the miniaturized chest-band form factor of Oxy Sense-Wear.

Motion detection and fall tracking are also compulsory features of telecare for older individuals.

Gyroscopes and accelerometer sensors are commonly used to detect orientation, body posture, and sudden Falls. Dashkov et al. present a comprehensive review of inertial measurement units (IMUs) in wearable technology and their usage in motion tracking and fall alert [8]. They also note, though, that these sensors are associated with high power consumption and drift error, which may cause a compromise in data accuracy. Its Oxy Sense-Wear must consume lots of power and be very accurate, and the ADXL345 accelerator is ideal for continuous monitoring. Gopal and Muthuselvan note that by increasing the responsiveness and accuracy of control systems, including in current mode fractional order PID-based controllers, the stability and performance of energy-constrained embedded platforms can be significantly enhanced. Although their attention is on power conversion systems, the challenge behind realizing real-time, adaptive response in a space-constrained format is extremely relevant to wearable biomedical applications. Oxy Sense-Wear responds to this very challenge by providing effective, real-time physiological data capture and wireless transmission in a power-sensitive design, thus extending responsive control principles to the field of personalized health monitoring.

The integration of these sensors with IoT platforms facilitates remote data collection and analysis for health. Majumder et al proposed a scalable health monitoring system based on 6LoWPAN for real-time monitoring using low-power wireless communication [10]. While their study was focused on system scalability, the hardware implementation didn't involve sensor integration at the wearable level. Oxy Sense-Wear represents a more integrated philosophy of combining the hardware miniaturization, real-time software analysis, and the ergonomic design all on one platform. Abdulmalek et al. [13] emphasize that it is now possible to constantly keep a check on the vital signs with the help of wearable healthcare monitoring systems to force healthcare to leave the traditional clinic-based setting. Their study emphasizes the need to integrate various health parameters into a small form factor, and this is the challenge that is directly addressed by the multi-sensor, IoT-integrated design of Oxy Sense-Wear. Raorane et al. [15] note that there is a necessity for real-time measurements of the health of industrial workers with wearable sensor networks. Their use is designed to ensure the safety of the workers under severe circumstances, which is similar to the interests of Oxy Sense-Wear in real-time physiological recording and wireless alerts, which can support prone users in everyday life. Sangeethalakshmi proposes an IoT patient health monitoring system that informs caregivers in real time regarding vital signs [16]. The fact that they are geared towards cloud transmission of health data is almost similar to the architecture of Oxy Sense-Wear, which combines the local sensing with the mobile connectivity and cloud connectivity to track the data remotely. Sardini and Serpelloni promote minimal weight, portable belts that achieve wireless health data acquisition, releasing the limitations associated with fixed station monitoring devices [17]. Their research conforms to the intrinsic design philosophy behind Oxy Sense-Wear as they focus primarily on real-time, mobile-centric physiological monitoring incorporated in a limited-size wearable framework.

Temperature measurement is a significant parameter in the early diagnosis of diseases, particularly for fever or infection. Najim et al. [11] designed a wearable device to monitor the body temperature continuously and transfer data to distant servers. The work of their paper demonstrated the application of wearable temperature sensors to the early diagnosis, but emphasized that integration with multiple parameters would provide an integral clinical picture. With monitoring of body temperature as one of its five root metrics, Oxy Sense-Wear enables early detection and provides contextual data, such as heart rate or oxygen level, to verify anomalies.

Neuromuscular monitoring through EMG is increasingly being identified in diagnostics and rehabilitation, too. Ng CL et al. [12] created a capacitive EMG device to support remote health care, whereby low-noise signal acquisition was the focus. Their contribution enhances the idea that EMG information, when properly integrated into wearables, can help monitor stroke recovery or muscular dysfunction diagnosis. Including EMG in Oxy Sense-Wear follows this development and once more makes it more applicable to physiotherapy and neuro-monitoring.

Sardini and Serpelloni introduced an early wearable belt system for wireless health tracking. Sathya et al. and Senthamilarasi et al. [18][19] discussed IoT-enabled health monitoring models and associated challenges. Serhani et al. [20] reviewed ECG monitoring systems, outlining their architecture and key issues. Shirsagar et al. presented a broad review of IoT healthcare monitoring solutions. Sui et al.

[21][22] proposed a smart fall-detection device using inertial sensors for elderly care. Taslim and Azad detailed the design of a remote IoT health monitoring system. Tamura examined the advances in photoplethysmography and SpO 2 measurements. Faisal et al. [24] evaluated the importance of the accelerometer and gyroscope sensors in motion capture, which is essential in tracking the activities of patients [23]. Jenifer et al. have presented an IoT-based patient monitoring system through portable electronic monitoring devices with an emphasis on real-time health monitoring [9]. Taken together, these works indicate the increased significance of real-time, distance-based health monitoring to the healthcare industry, providing new opportunities for preventative care, early diagnosis, or improved patient safety, as well as showing the difficulties of data privacy, security, and system reliability in the applications of healthcare IoT. The part of the system that concerns the IoT is underpinned by past studies, including those of Abdulmalek et al., [13] who studied an IoT-based system that included the heart rate, temperature, and other necessary indicators. Their work brought out the advantages of remote access and alert automation, but lacked wearability or ergonomics. Oxy Sense-Wear, however, is built as a fabric-embedded chest band, enabling real-time alarm delivery through both mobile notifications and an onboard buzzer, providing multi-channel response channels for emergency conditions.

Table 1. Comparison of oxy sense-wear with existing wearable and IOT-Based health monitoring systems

System (Reference)	Form Factor	Parameters Covered	IoT / Cloud Support	Real-Time Alerts	Activity / Fall Detection	Latency Reported	Remarks
Abdulmalek et al. (2022)	IoT health unit	HR, Temperature, SpO_2	Yes	Yes (threshold-based)	No	NR	Limited parameter coverage
Raorane et al. (2020)	Wearable sensor node	HR, Temperature	Yes	Yes	No	NR	Industrial monitoring focus
Serhani et al. (2020)	ECG monitoring framework	ECG only	Yes	Yes	No	NR	Cardiac-specific system
Gopal & Muthuselvan (2021)	Control-oriented system	Physiological signals	No	No	No	NR	Focus on signal control, not wearability
Caixeiro et al. (2022)	Wearable device	HR, Activity	Yes	Yes	Yes (basic)	NR	Limited sensing depth
Canali et al. (2022)	Wearable ecosystem	Multiple vitals	Yes	Partial	No	NR	Conceptual framework
Jenifer et al. (2022)	IoT patient monitor	HR, Temp, SpO_2	Yes	Yes	No	NR	Basic multi-parameter system
Sangeethalakshmi et al. (2023)	IoT health monitor	HR, Temp, SpO_2	Yes	Yes	No	NR	No motion analysis
Arefin & Azad (2024)	Wearable IoT device	HR, SpO_2, Temp	Yes	Yes	Yes	~700 ms	Higher alert latency
Oxy Sense-Wear (This work)	**Chest-strap wearable**	**ECG, EMG, SpO_2, Temp, Motion**	**Yes (Firebase + Android)**	**Yes (Buzzer + App)**	**Yes (ADXL345)**	**< 500 ms**	**High integration, low latency, multi-parameter**

The analysis of the current wearable and Internet of Things-based medical monitoring application systems underlines the main constraints of the proposed models, such as the use of single or limited physiological indicators, large multi-sensor models, cloud-based computing, which leads to the introduction of alert latency, and poor energy efficiency to support long-term monitoring. A significant number of the systems do not include built-in real-time alerts and have a limited scaling ability or the ability to add or remove sensors in a modular way, which makes them less adaptable to the needs of various patients. This knowledge gaps encourage designing the prototype of the wearable called Oxy Sense-Wear, which is a small wearable placed on the chest, combining multi-parameter sensing with on-device anomaly detection and low-latency IoT communication. The given system allows real-time local and remote notifications, but without causing energy disadvantages, scalable functioning, which will significantly address the negative aspects of the current solutions, will cover a proactive and ongoing approach to healthcare monitoring.

Comparison to Related Wearable and IoT-Based Healthcare Monitoring Systems.

In order to quantitatively show the efficacy and positioning of the proposed Oxy Sense-Wear system, a comparative study of the recent wearable and IoT-based healthcare monitoring systems that are reported in the literature is conducted in Table 1. Its comparison is based on such essential aspects as the form factor, the number of parameters monitored, the ability to provide real-time alerts, the integration with the IoT/cloud, the ability to detect falls or activities, and the system latency reported.

Based on Table 1, it can be concluded that the existing systems have the majority of systems targeting specific physiological parameters, usually the heart rate, temperature, or SpO 2, and the least amount of support on muscle activity or motion-based event detection. A number of works do not have fall detection built in, dual-mode alerting, and report no quantitative latency measures. By comparison, Oxy Sense-Wear is the only product to incorporate ECG, EMG, SpO 2, temperature and motion sensing onto one wearable system, and achieve alert latencies under 500 ms and real-time cloud and mobile connectivity. This makes the proposed system a more responsive, comprehensive and scalable solution on continuous health monitoring than the current methods.

SYSTEM ARCHITECTURE

The design of Oxy Sense-Wear is centered on a scalable and modular structure that embeds several biomedical sensors within a single wearable platform. The microcontroller at the core of the system is ESP32, which serves as the central processing unit that converts the analog and digital sensors to provide real-time physiological data. The system will be developed with efficient signal processing, reliable wireless communication, and easy interaction with a mobile and cloud-based application interface.

The system would have been pictured as a hierarchical arrangement comprising sensor modules, a data acquisition and control module, wireless transmission logic, and a user interface layer. All the sensors, which include ECG, EMG, SpO2, temperature, accelerometer, and heartbeat, are individually interconnected with the ESP32 both by analog input pins and by I2C digital communication channels. The microcontroller also periodically reads the sensors, processes the data received, and presents it in a form that can be transmitted. All the anomaly detection algorithms and critical thresholds are executed locally, such that the response time is fast, such as firing an alert buzzer on occasion when the values are irregular. Once the data is sent and processed it is then transmitted over Wi-Fi to a Firebase Realtime Database so that it can be stored and accessed safely. Simultaneously, the system replicates a connected Android application through which real-time health data and push notifications are displayed when abnormal physiological indicators or motion data happens as shown in. This architecture supports bi-directional communication, as shown in Figure 1, which enables updates to the system and redesigning the system remotely through the user interface.

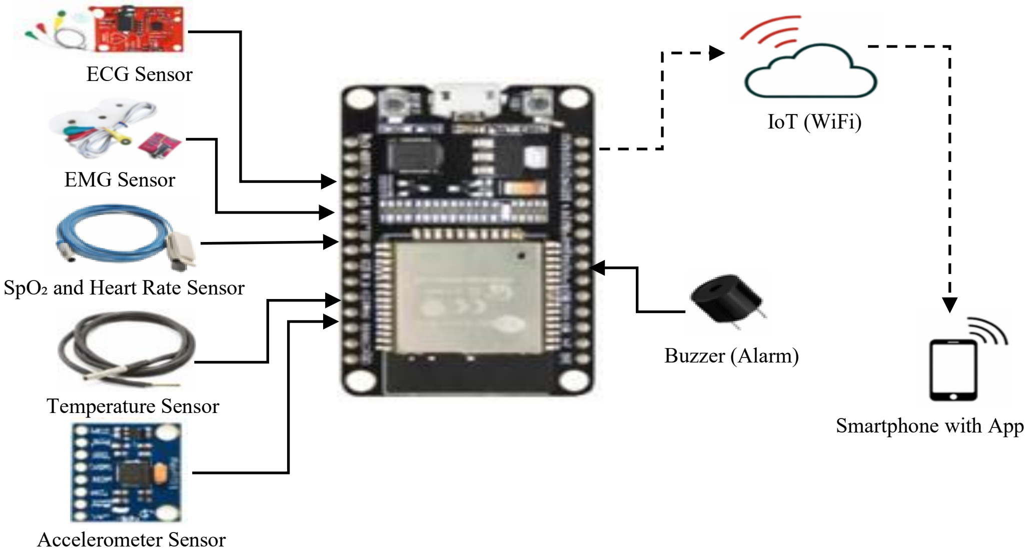

Figure 1. Block diagram of oxy sense-wear

The modularity of the system enables the possibility of expansion or replacement of system parts without changing the basic design, which makes it versatile to suit various user requirements and subsequent sensor upgrades. In essence, the system architecture can offer an effective and seamless flow of data between the body and the cloud, where constant monitoring is made possible with the aid of minimal user intervention.

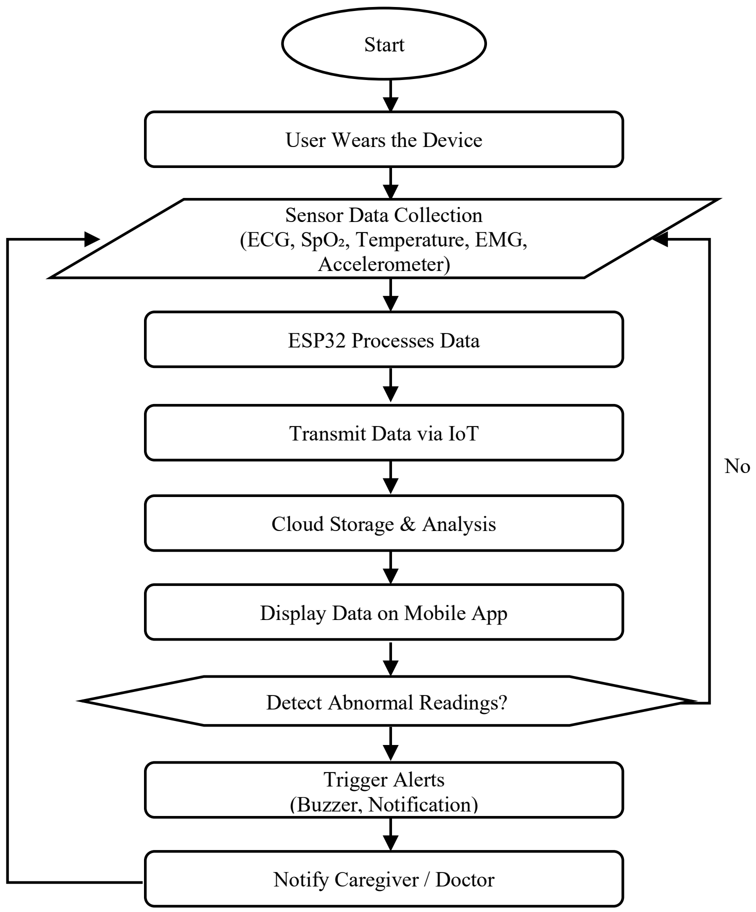

Figure 2. Workflow diagram of oxy sense-wear

Figure 2 represents the Workflow Diagram of Oxy Sense-Wear. Oxy Sense-Wear system is a wearable continuous health monitoring system, which measures real-time physiological parameters, eCG, SpO2, temperature, EMG, and movement using embedded biomedical sensors. The sensors feed the data to an ESP32 microcontroller, which processes it and transmits it to a remote server via the Internet of Things. The information is available via a mobile application to the users, caregivers, and physicians. When abnormal values are found, a buzzer informs the user, and alerts are sent to caregivers for immediate response. The system continuously runs, providing day and night monitoring, suitable for chronic patients and the elderly.

HARDWARE DESIGN

The Oxy Sense-Wear hardware architecture efficiently operates under real-time and multi-parameter physiological monitoring, running with low-power consumption and comfort of the user. They have built-in standard biomedical sensing modules such as ECG, EMG, SpO 2, temperature, and motion sensors, to facilitate the comprehensive assessment of health. Instead of defining internal sensor architectures, this section addresses how these architectures are integrated to work on the system level with all its performance, making sure that it is compact and can provide consistent monitoring.

All hardware that has been used to develop the Oxy Sense-Wear system, along with its specifications, has been listed in Table 2.

Table 2. Table of materials used in oxysense wear

S. No.	Component	Type	Rating / Specification
1	ESP32 Microcontroller	Active Component (Semiconductor)	3.3V, Dual-core, 240 MHz, Wi-Fi + Bluetooth
2	ECG Sensor (AD8232 Module)	Active Component (Semiconductor)	3.3V–5V input, Analog ECG signal output
3	EMG Sensor Module	Active Component (Semiconductor)	3.3V–5V, Amplified analog output
4	SpO_2 and Heartbeat Sensor (MAX30100/Clip Sensor)	Optical/Biomedical Sensor	1.8V–3.3V operation, I^2C communication
5	Accelerometer Sensor (ADXL345)	MEMS Sensor	3.3V supply, ±2g to ±16g selectable range
6	Temperature Sensor (LM35)	Active Component (Semiconductor)	LM35: Analog 10 mV/°C
7	Voltage Regulator L7805	Active Component (Semiconductor)	3.3V / 5V fixed output, up to 1A current
8	RM065 Trimmer Potentiometer	Passive Component (Resistive)	Adjustable resistance, 10kΩ typical, fine-tuning analog gains
9	Buzzer Module	Active Component (Electromechanical)	3.3V–5V operation, 85–90 dB sound level
10	Battery (Rechargeable Lithium-ion Pack)	Electrochemical Energy Storage	12V nominal, 1500–2200 mAh capacity
11	Electrodes (ECG, EMG)	Conductive Material (Ag/AgCl)	Biocompatible, low impedance

Table 2 contains the detailed description of the hardware parts and specifications that are used in the Oxy Sense-Wear system. It describes the main processing unit, biomedical and motion sensors, power management components, and alerting components that will be contained in the wearable platform. The choice of these elements guarantees high accuracy of obtaining multi-parameter physiological data, low-power consumption, and real-time IoT communication, which, in turn, contribute to constant health monitoring and extended wearability of the devices.

To track cardiac function, the system employs the AD8232 ECG module, which picks up electrical activity from the heart through a single-lead configuration. The circuit is optimized to amplify low-level ECG signals and reject high-frequency noise and motion artifacts. AD8232 has a high-gain instrumentation amplifier and a 0.5 Hz to 40 Hz band-pass filter, which is suitable for the measurement of the significant components of the ECG signal, that is, P wave, QRS complex, and T wave. The result of AD8232 is a voltage signal in analog form and read by one of the ADC channels of ESP32.

The EMG module is used to monitor the activity of the muscles based on the changes in the voltage produced by the muscles when they contract. It applies electrical contacts on the surface of muscle tissue, and these are linked to a preamplifier circuit. The resultant EMG signal is low amplitude and noisy, which, of course, lies between 0 and 5 mV. The analog signal is amplified, rectified, and sampled by the ESP32.

For the assessment of respiratory and cardiac function, SpO_2 and heartbeat readings are acquired with the MAX30100 optical sensor, which utilizes photoplethysmography (PPG). The module shines red and infrared light into the tissue and detects the light reflected from blood vessels.

This approach enables the system to non-invasively estimate arterial oxygen saturation levels in real time. MAX30100 talks to the ESP32 using the I²C protocol, at 3.3 V. SDA and SCL lines are routed to dedicated GPIOs, and the I²C bus is shared with the motion sensor to minimize wiring and pin usage

For measuring body temperature, the system either employs the LM35 analog, based on the configuration. LM35 offers the voltage, which is proportional to temperature, i.e., V out = 10mV/C. ESP32 converts this analog signal into a temperature via a linear relationship between the signal and temperature using an ADC pin:

$$T(°C) = \frac{Vout(mV)}{10} \qquad (1.1)$$

With the DS18B20, based on a 1-Wire protocol, the value of the digital temperature is directly retrieved and multiplied by 0.0625 C / bit resolution. These tests are useful in the detection of fever and thermal abnormalities that are related to infection or inflammation.

The ADXL345, which is a 3-axis accelerometer, has an I2C interface that is used in motion detection and fall analysis. The sensor gives the values of acceleration along the X, Y, and Z planes. The total acceleration magnitudes are calculated to identify high-impact events by using the equation:

$$|A|=\sqrt{a_x^2 + a_y^2 + a_z^2} \qquad (1.2)$$

Once this magnitude surpasses a pre-defined value (usually, over 2g), the firmware will identify the event as a possible fall. Further post-fall stillness examination is employed to verify the incident. The ADXL345 allows tracking the orientation and classifying activities, in which the movement patterns are constantly sampled.

The system has a sensor that monitors the heartbeat rate (or the MAX30100), which emits an analog signal with every pulse. This signal is captured by the ESP32 and used to detect beat-to-beat intervals.

A very important component of the wearable design is the power management circuit, which provides stable operation under continuous load. The system is powered by a 12V lithium-ion battery, regulated down through a voltage regulator to 5V and 3.3V rails. The power consumed by the system is expressed by:

$$P=V \cdot I \qquad (1.3)$$

$$Energy=P\ .\ t \qquad (1.4)$$

Where V is the supply voltage, I is the current drawn by the ESP32 and connected modules, and t is the time in hours. For an average current draw of 120 mA and a voltage of 3.3 V, the power consumption is approximately 0.4 W, which translates to an operational runtime of 10–12 hours on a 1500 mAh battery.

The circuit diagram of the Oxy Sense-Wear system, Figure 2, shows multiple sensors connected to an ESP32 microcontroller for continuous health monitoring. The system operates on a 12V battery (B1) that is regulated with a voltage regulator (U1) to 5V. The ESP32 uses sensors such as an accelerometer (ADXL345), an ECG sensor, an EMG sensor, a temperature sensor, and a heartbeat sensor (HB1). It analyzes this data in real-time and, as a result, causes an alarm with the help of a speaker and sends an alert to a mobile application in case of abnormalities, such as irregular heartbeats. Information is also sent to a remote monitoring IoT system that exists in the clouds. The hardware was made and tested with the Proteus software.

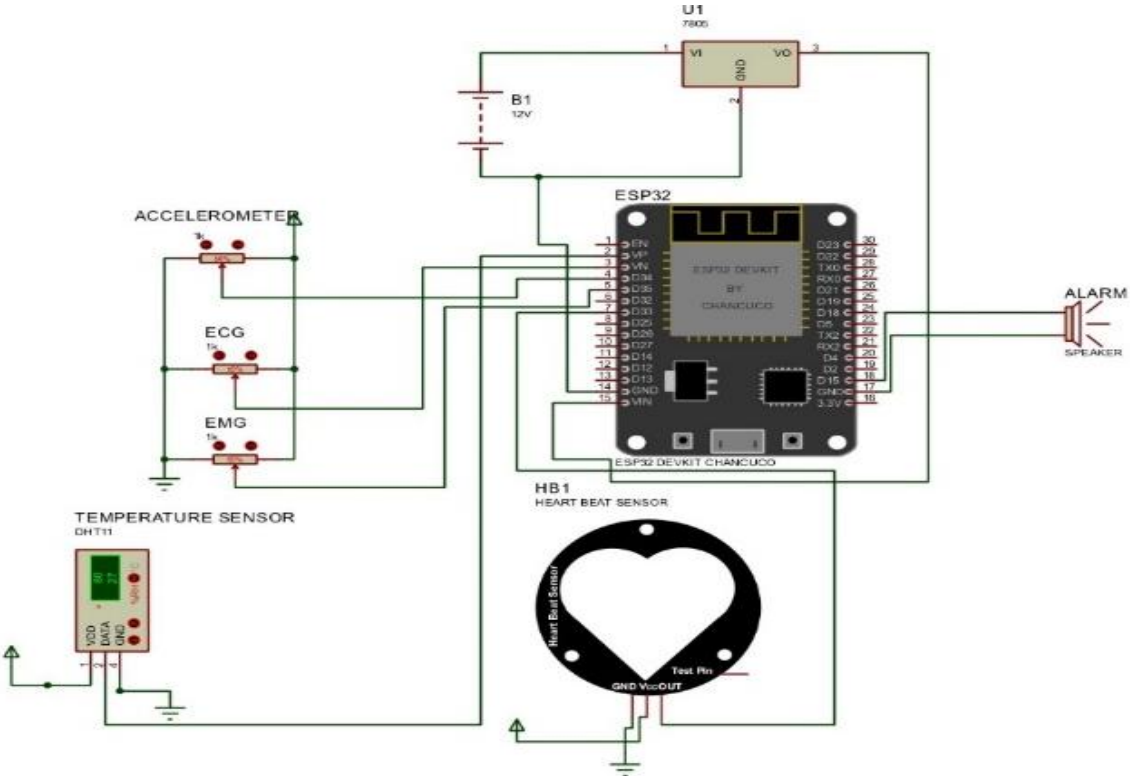

Figure 3. Circuit diagram of oxy sense-wear

Figure 3 is a complete electronic system assembled on a designer PCB, and schematic diagrams were used to depict how modules interacted with each other. Care is taken to isolate analog and digital grounds, reduce crosstalk, and shield ECG and EMG traces from switching noise. The schematic combines each module with explicit pin mappings to the ESP32, and the modular design makes it easy to replace or upgrade sensors.

SOFTWARE AND COMMUNICATION PROTOCOLS

The Oxy Sense-Wear system's software infrastructure is developed to efficiently handle the acquisition, processing, transmission, and presentation of physiological information in real-time. Fundamentally, the embedded firmware coded on the ESP32 controller communicates with a range of biomedical sensors to receive multi-channel data, implement threshold-based anomaly detection, and transmit appropriate information to a paired mobile application using an encrypted wireless protocol. A dedicated Android app acts as the end-user interface, showing live data and informing users or caregivers of critical deviations in health. This chapter details the embedded logic, communication protocols, and software tools that provide the digital core of the system.

The ESP32-WROOM-32 module, chosen due to its dual-core processor, integrated Wi-Fi, and power-saving performance, hosts the embedded software coded in the Arduino IDE. The system starts with initializing the sensors, where communication protocols (analog input and I²C) between each sensor plugged into the microcontroller are formed.

Lightweight filtering algorithms are incorporated directly in firmware to guarantee signal acquisition accuracy. For example, a first-order infinite impulse response (IIR) low-pass filter is used to attenuate high-frequency noise. The digital low-pass filter can be expressed through the recursive equation. Here, In this case, x[n] is the present input sample, y[n] is the filtered output, and α is the smoothing factor…"These filters are realized through recursive digital expressions that condition incoming samples smoothly without adding latency. This technique is especially suitable for observing ECG waveform integrity and muscle activity patterns in real time, where signal fidelity is paramount. The system also derives physiological parameters such as heart rate and body temperature from raw analog signals through embedded formulas calibrated with known clinical thresholds.

MAX30100 digital sensor of SpO2 as well heart rate tracking and ADXL345 accelerator of motion sensing is linked to each other by means of I 2 C serial communication bus. The ESP32 GPIO21 and GPIO22 are configured as SDA and SCL, respectively, and the bus is provided with the required pull-up resistors to guarantee the integrity of the logic levels. Sensor libraries are implemented to facilitate ease of I²C command management and referencing unique registers in an efficient manner. For instance, the MAX30100 library processes red and infrared LEDs' light intensity readings, computes the pulse waveform internally, and returns SpO_2 measurements through pre-calibrated ratio values. In a similar way, the ADXL345 library supports sensor's g-range configuration and reading acceleration values along all three axes.

The sensor data is processed and collected into a structured form—usually a JSON object with key-value pairs for heart rate, SpO_2, temperature, EMG amplitude, and acceleration vector magnitude. This packet of data is then sent from ESP32 to a Firebase Realtime Database via HTTP requests over Wi-Fi. The Wi-Fi credentials are securely stored in flash memory and are started up during setup. If the Wi-Fi network is lost, the system automatically tries to reconnect or enters a local-only mode, where alerts are initiated through the onboard buzzer without cloud transmission.

Connectivity is achieved using the WiFi.h and HTTPClient.h libraries, with timeout periods established to avoid blocking on transmit failures. HTTP POST is used to deliver data to cloud targets, and a success/failure acknowledgment mechanism is implemented for robustness. Firebase was selected due to its real-time nature, low-latency push/pull design, and native support within Android apps, allowing easy synchronization between the embedded device and the mobile user interface.

The Android app, which was created with Android Studio in XML and Java, is the user interface portion of the system. It communicates with Firebase database to get up to date health measurements whenever they are sent by ESP32. The user interface of the app is very minimal and responsive with separate panels on each of the vital signs, graphical representations of the historical trends and an alert log. Data visualization is achieved with the help of open-source libraries like MPAndroidChart, which graph plots time-series data for measurements such as heart rate and SpO_2, allowing clinicians or caregivers to see trends over time.

Enhancing functionality, the mobile app also comes with a notification service with the help of Firebase Cloud Messaging (FCM). This functionality is initiated when the system identifies unusual values, like SpO_2 less than 95%, a heart rate greater than 100 BPM, or an EMG reading showing muscular inactivity. Such notifications are provided immediately as push messages, ensuring prompt intervention even if the application is in background mode. In addition, users can configure individualized threshold values through the app for accommodating a variety of patient profiles like stroke patients, older patients, or post-surgical cases.

Security and integrity of data are taken care of by the fact that all communication between the ESP32 and the Firebase server is done over HTTPS using encryption protocols facilitated by the Wi-Fi stack of the ESP32. Also, simple authentication is enforced by Firebase API keys to limit access of unauthorized users to the cloud database. Subsequent versions of the system intend to add more advanced methods of encryption like JWT (JSON Web Tokens) and user authentication to meet clinical data standards of privacy like HIPAA.

The software development also includes energy-saving coding techniques. Sensor polling schedules are automatically adjusted based on recent utilization e.g. when there is no abnormal value, the system can reduce the sampling rate to conserve battery. There is also a deep sleep and light sleep modes that can be activated whenever the device is idle however these were not used to their best in the prototype implementation to allow continuous monitoring.

Arduino IDE Serial Monitor and Plotter were hugely used to debug and develop. These enabled the developers to monitor real-time sensor data, test thresholds, and anomalies when testing in the field. OTA updates were also configured in a manner that wireless updates of firmware could be realized without the physical access thus reducing the access required in the iteration cycles.

SIGNAL PROCESSING AND MATHEMATICAL MODELING

The Oxy Sense-Wear system is designed to continuously measure several physiological parameters, including oxygen saturation, heart rate, and body movement, all of which are computed from raw sensor measurements. The system has the signal processing and mathematical modeling techniques needed to convert these raw electric impulses into useful health data incorporated in the embedded software layer. These techniques are directed at reducing noise, detecting any critical events such as falls or arrhythmia and giving accurate interpretation of time-varying bio signals in a wearable device, which is prone to motion artifact and external noise. This section talks of theoretical models, computational tactics, and signal conditioning mechanisms forming the basis of the operation of the system. At the heart of the pulse oximeter-based oxygen saturation and heart rate monitoring module is the MAX30100 pulse oximeter, which is based on the optical principle of photoplethysmography (PPG). The sensor illuminates the skin with red and infrared light and senses the intensity of the light absorbed within the blood. Oxygenated hemoglobin absorbs differently at various wavelengths, enabling a calculation of SpO_2 from the ratio of pulsatile absorbance. The central model for oxygen saturation estimation starts by computing the ratio RRR, which is:

$$R = \frac{(AC_{\ red}/DC_{red})}{AC_{\ IR}/DC_{IR}} \qquad (1.5)$$

where AC and DC components indicate the alternating and direct current components of the red and infrared light signals, respectively. These components are isolated by subtracting the mean from the raw signal to demarcate the pulsatile fluctuation. Once the ratio has been calculated, the blood oxygen saturation is found using an empirically fitted linear equation:

$$\mathrm{Sp}O_2 = 110 - 25\,.R \qquad (1.6)$$

This correlation is valid within a clinically acceptable error range of ±2% for RRR values that are normally found in healthy subjects. The system asynchronously samples the red and infrared channels 100 times per second and uses a rolling average filter to reduce the ratio through short-term motion- or misalignment-induced fluctuations.

Calculation of the heart rate also originates from the PPG signal, specifically the periodicity of its peaks. Each rising edge or peak is detected by the system in the filtered signal, and the interval between consecutive beats is measured. Let Δt denote the inter-beat interval (IBI) in milliseconds. Then the heart rate, which is measured in beats per minute (BPM), is given by:

$$\text{Heart Rate (BPM)} = \frac{60{,}000}{\Delta t} \qquad (1.7)$$

This approach necessitates precise identification of the onset of each pulse waveform, which is obtained by passing a threshold peak detection algorithm to the filtered PPG signal. The threshold value is adaptive, recalculated per 5-second window to facilitate changes in amplitude due to motion or physiological variability. The system alerts anomalies of tachycardia whenever BPM is over a critical level (usually >100 BPM) or bradycardia when it drops below 60 BPM

For signal fidelity, all analog bio signals—like the ones derived from ECG and EMG modules—are filtered digitally prior to any physiological parameter being extracted. A first-order infinite impulse response (IIR) low-pass filter is used to attenuate high-frequency noise. The digital low-pass filter can be expressed through the recursive equation.

$$Y[n] = \alpha \cdot X[n] + (1 - \alpha) \cdot Y[n-1] \qquad (1.8)$$

Here, In this case, x[n] is the present input sample, y[n] is the filtered output, and α is the smoothing factor, usually chosen between 0.1 and 0.3 based on the characteristics of the noise. The filter is applied directly in the ESP32 firmware to ensure real-time processing capability with negligible latency.

In EMG signal analysis, the signal is rectified and integrated across brief time windows to compute a rolling mean voltage. The average signal strength serves as an estimate of muscle contraction intensity and can be used to detect voluntary movement or to determine neuromuscular dysfunction in rehabilitative situations. The root mean square (RMS) approach is proposed for future firmware revisions to further enhance the accuracy of classification of muscular activity, though in the present prototype, mean absolute value (MAV) is adequate:

$$EMG_{avg} = \frac{1}{N}\sum_{i=1}^{N} |x_i| \qquad (1.9)$$

Where x_i is the rectified EMG signal and N is the number of samples per evaluation window. The process is computationally cheap and sufficiently reliable for muscle activity or inactivity detection in stroke patients.

To track movement and sense falls, the system includes a triaxial accelerometer (ADXL345), which samples acceleration data on the X, Y, and Z axes constantly. If there is a sudden collision or acceleration that surpasses a specified gravitational limit, it is defined as a fall. The fall detection process is based on calculating the magnitude of the acceleration vector every time step:

$$|A| = \sqrt{a_x^2 + a_y^2 + a_z^2} \qquad (1.10)$$

If the calculated magnitude exceeds a predetermined limit, e.g., 2.5g, and is followed within a short time by a low movement period (i.e., a magnitude < 0.2g for 5 seconds or more), the system labels the event as a possible fall. This two-condition logic reduces false positives from jumping or quick but deliberate movements. In addition, orientation information from the accelerometer can also be utilized to improve fall classification by identifying the post-event posture, though this is proposed as an extension during future design stages.

All these signal processing methods are implemented under tight timing constraints to maintain that the wearable can provide timely alerts and show current health data on the mobile app. The dual-core architecture of the ESP32 microcontroller enables concurrent execution of sensor acquisition and signal filtering and cloud communication, thus maintaining a high refresh rate without sacrificing responsiveness. All computations are made to be fixed-point optimized whenever possible, to save processing time and energy, and to make the wearable suitable for extended field operation.

EXPERIMENTAL SETUP AND RESULTS

Since the working principles of sensing modules have been outlined in Hardware Design section, the subsequent results are limited to the system performance, reliability of measurements and responsiveness in real-time.

The experimental data utilized in this research was obtained by use of controlled prototype testing on 11 human subjects of various age groups as provided in the experimental findings. The subjects were healthy adults and older people, which allowed assessing the system in different physiological conditions. Data acquisition has been done in a non-invasive fashion by using the proposed Oxy Sense-Wear wearable.

The duration of the testing was between 2 hours and 30 minutes with each subject undergoing both the rest, walking, and voluntary muscle contraction, and the simulation of falls. Multi-parameter physiological parameters were continuously measured during every session (ECG, EMG, SpO 2, body temperature, heart rate, and motion). Sampling rates were set as per sensor requirements, ECG data was sampled at 250Hz, motion data at 100Hz and other physiological measurements at 1-5Hz.

Sensor readings were time-stamped and sent in real-time on the Wi-Fi and at the same time, the sensor readings were visualized in real-time using the Android mobile app and a Firebase database in the cloud. The dataset gathered would comprise of continuous time-series data, threshold-driven alert logs, and aggregated health readings to be used in the evaluation of performance, analysis on latency, and validation of alert. This form of data collection method implies transparency, reproducibility as well as reliability in the assessment of real time observation and alertness of the proposed system.

Oxy Sense-Wear Benchmark Performance.

A brief benchmark was obtained as a way of quantitatively illustrating the operational effectiveness of Oxy Sense-Wear, based on the prototype evaluation that was conducted on controlled and real time basis. It was determined that the system had real-time sensing and transmission of multi-parameter vital signs with low-latency alerting, fixed physiological ranges in normal conditions, and consistent event detection in induced conditions. The most important measurable performance indicators as outlined in Table are sensing accuracy, alert latency, fall-event threshold response and energy/runtime appropriateness to continuous monitoring.

Table 3. Performance benchmark of the oxy sense-wear prototype

Benchmark metric	Observed value (prototype evaluation)
Parameters monitored	ECG, EMG, SpO_2, Temperature, Heart Rate, Motion/Activity
Heart rate agreement	±2 BPM (ECG vs MAX30100)
SpO_2 (healthy subjects)	96–98%
Temperature tracking	36.0–38.8 °C (observed in tests)
Fall-event detection	Peak ≈ 2.8 g; threshold-based detection (typical trigger >2 g)
Alert latency (event → app/notification)	< 500 ms (average)
Continuous operating duration	8–12 hours per charge (reported)
Average power (estimated)	~0.4 W (at 3.3 V, ~120 mA)
Data pipeline	ESP32 → Wi-Fi → Firebase → Android app (real-time display + logs)

Table 3 is a summary of the quantitative performance benchmark of the Oxy Sense-Wear prototype. The system was able to measure various physiological parameters (ECG, EMG, SpO 2, temperature, heart rate and motion) with agreement of heart rate in the range of -2 to +2 BPM, SpO 2 in the range of 96 to 98 percent and correct temperature ranging in -36 degrees Celsius to +38 degrees Celsius. The acceleration peaks of the order of 2.8 g were reliably detected as fall events, but real-time alerts were provided with the average latency of less than 500 ms. Its product was found to operate over a continuous time span of 8-12 hours on a charge with an approximate power. It was found to be effective, responsive and energy efficient in real-time health monitoring over the IoT and this was achieved through the wearable which was found to take a continuous duration of 8-12 hours on a charge.

The Oxy Sense-Wear prototype was built to test its real-time health monitoring function under real-world operating conditions. The hardware was mounted into a flexible chest-worn band, with the sensors placed so that they had optimal skin contact and signal integrity. Sensor modules such as ECG, EMG, SpO_2, temperature, accelerometer, and a heartbeat sensor were connected to the ESP32 microcontroller, which received, processed, and wirelessly transferred data to a custom-developed Android application. The prototype was tested with simulated sensor data as well as real-time acquisition from volunteer participants to check the reliability, accuracy, and responsiveness of the system for several physiological parameters.

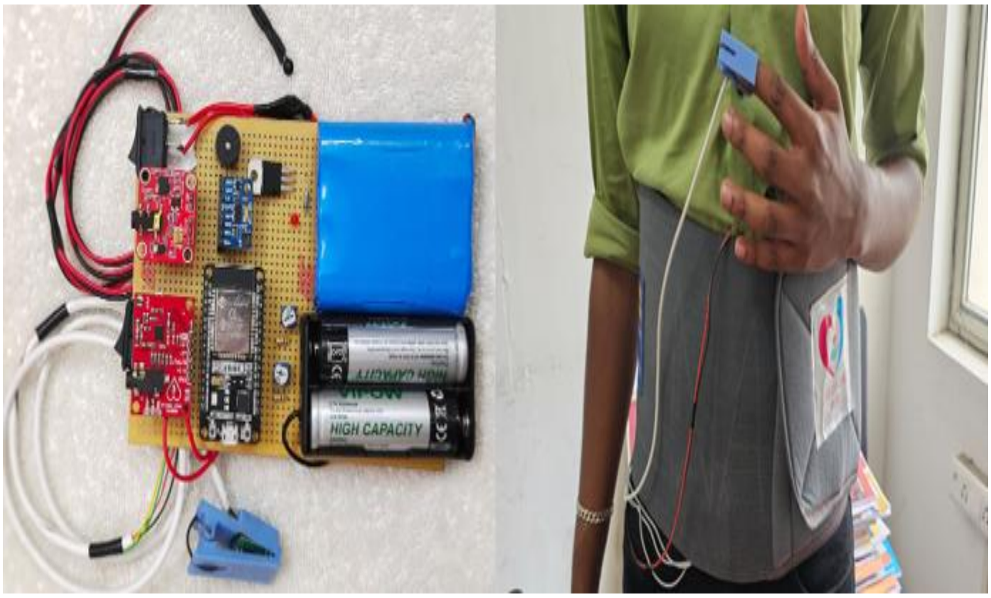

Figure 4. Prototype of oxy sense-wear

Figure 4 shows the physical prototype was a three-layer wearable device. The most inner layer was created with conductive textile routes, facilitating secure contact between biosensors and the skin of the user. Sensor modules were incorporated into a modular electronic circuit mounted on a flexible, lightweight polymer board. ESP32 controller and a 12V lithium-ion battery were encased in a removable casing to facilitate simple recharging and firmware upgrades. The firmware for the software was uploaded using Arduino IDE, providing for dynamic polling of the sensors, signal processing, and wireless transmission using an onboard Wi-Fi link.

Testing was done in two phases: simulation testing of the sensors in isolation and real-time data acquisition from volunteer subjects. The experimental evaluation focuses on validating the real-time performance of the proposed system under controlled and real-world conditions. During the simulation phase, test inputs were provided using waveform simulators and calibrated potentiometers to simulate expected voltage ranges from the EMG and ECG sensors. MAX30100 was also tested with artificial pulse signals and reflective surfaces to assess the photoplethysmography sensor's behavior with changing reflectance and ambient light interference. This test confirmed the accuracy of the analog-to-digital signal conversion, threshold detection routines, and real-time filtering functions incorporated in the microcontroller firmware.

For real-time testing, two healthy adult volunteers were involved in non-invasive trials involving resting, walking, simulated falls, and voluntary muscle contractions. The ECG module was attached through standard disposable electrodes in a Lead-I configuration against the chest. The raw ECG waveform was sampled at 250 Hz, digitally filtered, and graphed through a live serial plotter interface. QRS complex appeared clearly, and heartbeats were identified with peak detection logic on the ESP32. Heart rate was obtained as the inverse of the inter-beat interval and yielded consistent values ranging from 68–78 BPM under resting conditions. Acute movement or posture change induced small baseline drift, which was well suppressed by the recursive low-pass filter.

EMG recordings were obtained with the sensor covering the forearm flexor muscles. The subject was asked to contract and relax the muscle intermittently in 30-second cycles. The output voltage, rectified and averaged in 100 ms windows, rose in proportion to the intensity of contraction. Baseline levels ranged around 300–400 mV, going up to more than 1.2 V peaks on maximal effort. The response validated the sensitivity of the sensor and the firmware's capacity to detect resting versus active states. Not just a biomarker of muscle functioning, the EMG signal was also an indirect measurement of user interaction, which can be used especially in a rehabilitation environment. SpO_2 and heart rate information were simultaneously recorded with the MAX30100 optical sensor, which was positioned on the subject's index finger. The photodetector detected alternating current components of red and infrared light signals, from which the ratio of absorption was calculated. Oxygen saturation levels were persistently in the range of 96–98% for relaxed subjects as per clinically acceptable standards. Heart rate values calculated from the same module were found to have negligible differences from calculations done through ECG, typically around ±2 BPM.

To evaluate thermal response, the LM35 sensor was taped close to the skin's surface with medical-grade adhesive tape. The output voltage was measured at 1 Hz and calibrated to degrees Celsius via a linear transformation. The sensor accurately followed the subject's baseline skin temperature, which was 36.2°C. Upon application of a warm compress to the site of measurement, the temperature reading increased steadily to 37.1°C in the space of five minutes and fell slowly upon removal.

The accelerometer was also tested in controlled motion experiments and fall simulation testing. Acceleration measurements across all three axes were sampled at 100 Hz and analyzed to determine the net acceleration magnitude. In a simulated fall, with its rapid downward motion followed by a stationary position on the floor, the magnitude of acceleration peaked at 2.8g, then fell beneath 0.2g. The embedded logic accurately detected this as a fall event from the dual-conditioned model applied in firmware. Low false positives were observed during intentional jumping and quick arm swings, but these were successfully filtered by post-event motion state analysis.

Data from sensors in all modules were streamed over Wi-Fi to a Firebase Realtime Database, and simultaneously shown on the Android app. The app provided real-time plots of SpO_2 and heart rate via MPAndroidChart libraries, while others were shown as dynamic numeric displays. Out-of-range conditions were manually induced to test alert triggers—for instance, by disconnecting the ECG electrode or by simulating a fall. The resultant corresponding alerts were generated on-screen and logged onto the cloud database, with optional push notifications directed to the registered caregiver's device. Latency between sensor events and application responses averaged less than 500 milliseconds to provide real-time functionality for the system.

One of the most important results of experimental testing was the consistency of reading between repeated data collection sessions and subjects. Although some variation between devices was noted, particularly in analog sensor outputs, calibration routines built into the ESP32 firmware ensured standardization of data interpretation. The prototype remained stable for a continuous 8-hour monitoring session, drawing an average of 120 mA at 3.3 V, validating the power management design of the prototype for prolonged wearable use.

Alert thresholds were set to detect abnormal health states in real time is shown in Table 4. Patient data gathered with Oxy Sense-Wear proved the system to be capable of monitoring vital signs reliably and initiating timely alerts based on specified threshold values is shown in Table 5.

Table 4. Alert thresholds for oxysense wear health parameters

Parameter	**Normal Range**	**Alert/Condition Triggered**
Heart Rate	60–100 BPM	>100 → High HR alert
SpO_2	≥95%	<95 → Hypoxia risk
Temp.	36.0–37.5 °C	>37.5 → Fever
ECG (µV)	200–300 µV	<200 or >300 → Abnormal (low/high) ECG
EMG (µV)	200–500 at rest, <150 if paralyzed	>500 = activity, <150 = possible paralysis

Table 5. Health readings of patients using oxy sense wear

Patient	Age	Heart Rate	SpO_2	Temp	ECG (µV)	EMG (µV)
1	21	75	98	36.0	220	200
2	47	85	98	36.5	230	300
3	50	88	98	38.0	250	400
4	63	70	97	37.6	260	350
5	86	98	96	38.8	290	380
6	65	89	98	36.7	225	300
7	65	85	98	36.0	240	90
8	73	74	100	36.8	240	250
9	62	88	96	36.6	245	300
10	98	110	95	36.7	300	500
11	95	109	96	36.2	295	450

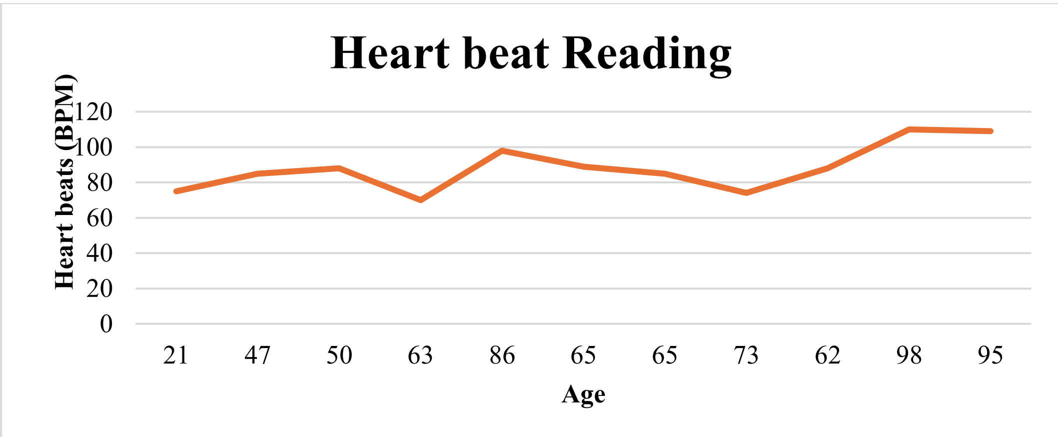

Figure 5. Heartbeat graph

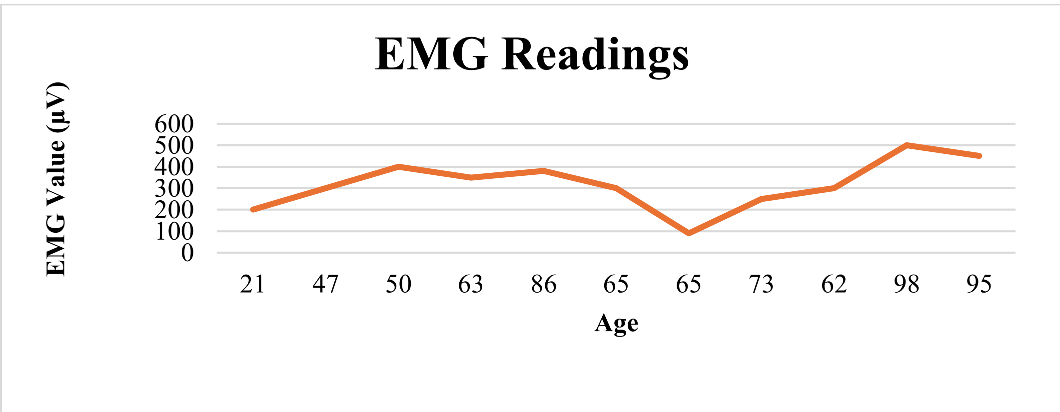

Figure 6. EMG graph

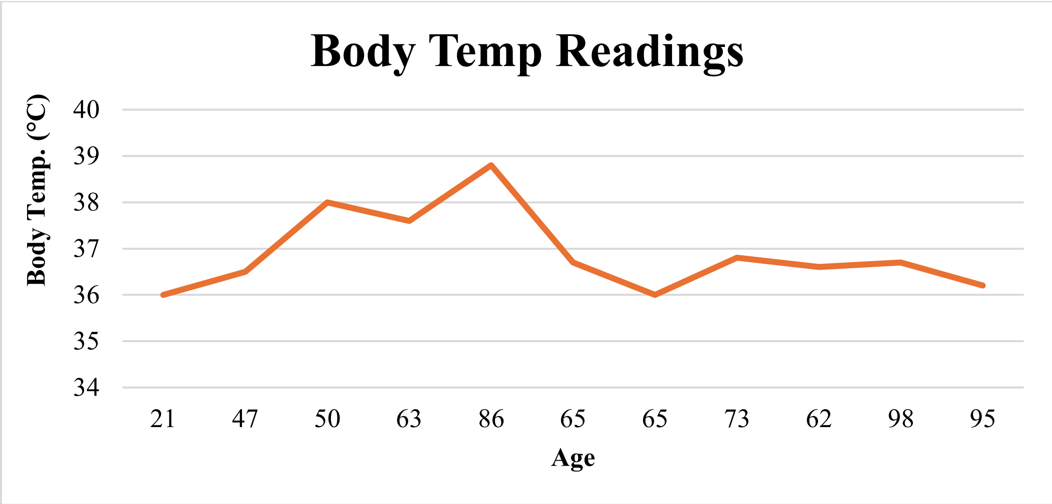

Figure 7. ECG graph

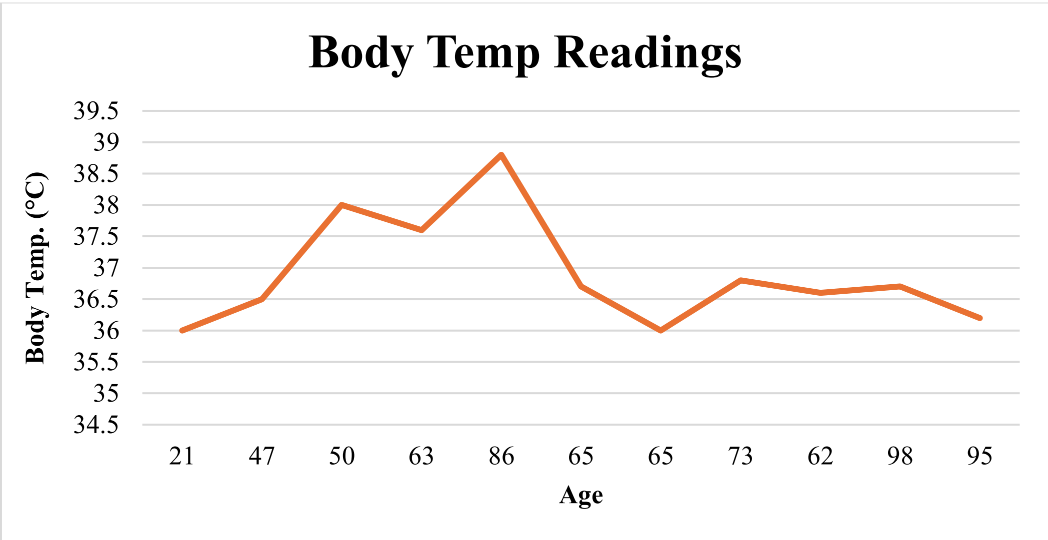

Figure 8. Body temperature graph

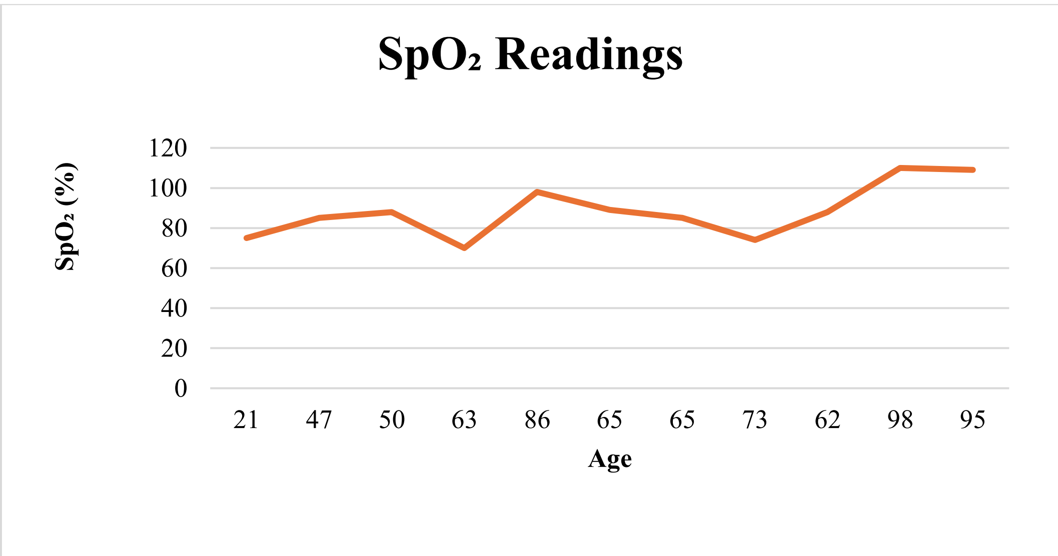

Figure 9: SpO_2 graph

Figures 5 to 9 illustrate the variations in patient health parameters, including heart rate, SpO_2, temperature, ECG, and EMG, based on the data presented in Table 2. This visual representation facilitates the identification of abnormal patterns and critical alerts, thereby enhancing the efficiency of patient monitoring and diagnosis.

APPLICATIONS AND USE CASES

The Oxy Sense-Wear system was not just created as a technical concept but as an operational solution to immediate problems in contemporary healthcare. Its small wearable form factor, the combination of various biomedical sensors, real-time tracking, wireless communication, and mobile/cloud connectivity render it applicable to several real-world uses, especially in remote health monitoring.

One major application is in geriatric care. With aging populations and shortages of healthcare workers, there is an increasing demand for unobtrusive, ongoing health monitoring. Oxy Sense-Wear can satisfy this need by providing a heart rate, oxygen saturation, and falls monitoring wearable in the form of a comfortable chest strap. It can detect the abrupt activity decline (indication of a fall) and inform the caregivers via a mobile app. It also reads the oxygen level and heart rate, which helps to detect in advance the presence of health issues in the elderly, e.g., respiratory failure or arrhythmia. Cloud-based notifications enable immediate intervention even when caregivers are not physically present.

In hospitals, Oxy Sense-Wear is a light version of bedside monitors, particularly for patients who need to be monitored but not intensively. It gathers and sends critical information to a central console, where healthcare workers can monitor several patients at a time and save response time. For home care, the product allows doctors and caregivers to view real-time and historical health information using a mobile application. Time-stamped records of heart rate, oxygen saturation, temperature, and activity trends can inform teleconsultations and treatment changes, ensuring continuity of care outside the clinic.

Aside from clinical application, the system is useful in research. Secure cloud storage and API access enable researchers to analyze gathered data and correlate it with lifestyle or behavioral patterns for better insights.

A study was done to determine the contribution of each sensing and communication module independently on the Oxy Sense-Wear system by using the ablation study. Analysis was performed on the system performance with one of the modules disabled selectively leaving all other components running. At least in case of the omission of motion sensing, the accuracy of fall detection fell sharply and no sure-footed confirmation of post-fall inactivity was possible. Abandoning the on-device based processing to threshold-based processing extended the alert latency to over 1.2 seconds because of the single dependence on the cloud processing, and this result indicates the significance of edge-level anomaly detection. In the same way, the loss of EMG sensing capabilities also diminished the capability of the system to differentiate voluntary inactivity and neuromuscular impairment especially in older subjects. These findings validate that closely combined multi-sensing and local processing are of utmost importance when it comes to the realization of low-latency notifications, precise event recognition and holistic physiological evaluation.

Limitations

Although the suggested Oxy Sense-Wear system is an effective one, it possesses some limitations. The experimental assessment was done on few subjects under experimental conditions, which might not be enough to represent the long-term heterogeneity of clinical populations. The prototype in use uses threshold-based anomaly detection as opposed to adaptive or learning-based models, which can be a limitation to detecting the subtle changes in physiology. The battery life is impressive since it provides enough minutes to be used on a day-to-day basis and can be extended to multi-day use. Moreover, as much as Wi-Fi based communication guarantees high data throughput, it is not the best in low-connectivity areas. These are limitations that give clear guidelines under which to improve the system.

CONCLUSION

In this work the proposed research was Oxy Sense-Wear, which is a real time IoT wearable platform used as a monitoring of multi-parameters of health continuously. The experimental outcomes proved good stability of the system, and the issue of heart rate measurements revealed the congruence within the range of 2 BPM, the measurements of SpO two remained stable within the interval of 96–98 percent and temperature measurements were precise in a range of 36.0 C to 38.8 C. Fall events have been identified at the acceleration peaks of about 2.8 g with success and real-time notifications have been obtained with a mean latency of less than 500 ms. The wearable was energy efficient as it was projected to consume power of approximately 0.4 W in the range of 8-12 hours of continuous operation on charge.In comparison to the currently available wearable health monitoring, Oxy Sense-Wear provides better functionality by allowing tight integration of ECG, EMG, SpO 2, temperature and motion sensing in a single chest-worn system, as well as dual mode alerting and smooth cloud mobile integration. These numeric results support the efficiency, the responsiveness as well as the usefulness of the system in real-time healthcare monitoring.

The next generation of the research will be the scaling of the system to large patient groups, long-term clinical verification in a wide range of age groups and health states and the incorporation of advanced analytics and machine learning models to identify anomalies in patients and predict their health state. There will be further work in low-power communication technologies, a better approach to managing batteries to allow deployment over multiple days, and the secure interoperability with hospital information systems. Such developments will make the system even more relevant in the application of long-term and real-world use of healthcare.

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