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Design of Smart Wearable for Cardiopulmonary Monitoring with Adaptive Feedback Loop

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ABSTRACT

The increasing worldwide problem of cardiopulmonary diseases adds even more sense to the necessity of safety and accuracy of health monitoring systems, which should be non-invasive and performed continuously and in real-time. This paper presents a new smart wearable product that is used to monitor cardiopulmonary vital signs, such as heart rate (HR), respiratory rate (RR), and peripheral blood oxygen saturation (SpO_2) with a multimodule wearable form factor, which is wearable and easy to use due to the implementation of miniature and low-power sensor modules. The fundamental innovation of the proposed system is an adaptive feedback loop of the system, which is supported by edge-based machine learning of anomaly detection modules, LSTM-based, allowing adjusting the alert thresholds and delivering the personalized perspective on health dynamics in real-time. As compared to standard wearables that apply fixed limits on the alarms, our solution is considering the physiological individual variations and changes over time, thus making it sensitive to early abnormalcy changes and reduces false alerts. The wearable comprises of an ESP32 microcontroller platform that enables the transmission of wireless data over Bluetooth to a companion mobile application in order to visualize data and issue alerts over a remote connection. The performance of the system was tested in the form of a mixture of simulations, bench-level hardware tests, and pilot research of 10 human participants with different cardiopulmonary status. Its measurements prove to be of high accuracy and more than 98% of correlation with conventional clinical devices, and the feedback loop of the device is responsive to highly critical variations in physiologic signals. Further, the system has low latency (<=130 ms), power efficient (<=45 mW) and solid signal processing with motion artifacts. Adaptive feedback mechanism also managed to issue an early alert regarding abnormal breathing pattern and oxygen desaturation in high-risk participants. The article is an important contribution to the future wearable health monitoring platforms with the possibility of proactive care, all-time health profiling, and remote patients management via connection to the telemedicine and e-health structures. The modularity and flexibility of the system also leave us with the potential that we use it in managing chronic diseases, with the aged, and during rehabilitation.

1. INTRODUCTION

Chronic obstructive pulmonary disease (COPD), asthma, congestive heart failure, and symptoms of obstructive sleep apnea are considered a few of the most devastating cardiopulmonary complaints throughout the world. Regular screening and monitoring of all important vital signs of the organism, including heart rate (HR), respiratory rate (RR), and blood oxygen status (SpO 2) is essential in the treatment of such conditions and improvement of related health risks. Historically, these parameters have been restricted to clinical observation in large and costly, not to mention invasive, instrumentation which further restricts their portability and long-term or ambulatory application. With healthcare systems transitioning to a culture of prevention, personalization, and decentralization of care, an urgent need to have wearable technologies can conduct accurate real-time physiological monitoring during the real-life setting has emerged.

The growth in microelectronics, low power, biomedical sensors, flexible electronics, and wireless communication are all relatively new technologies that currently allow wearable health monitoring systems to become feasible. The devices allow constant monitoring of vital signs, a non-invasive process to connect the patients with the health providers. The majority of the wearables available in the market are however passive data gathering and can only trigger alerts based on fixed set-points, and have no intelligence to be adaptive to the vagaries of individual physiology. Such method does not only cause a high false positive or false negative rates, but also ignores useful temporal dynamics in the biosignals that might be pointing at an early sign of health degradation.

To address the aforementioned restrictions, this paper (i) introduces the concept and implementation of a smart wearable system that has an adaptive feedback loop, that is, it analyzes real-time cardiopulmonary signals and adapts its response strategies to them. The suggested system couples a combination of biosensors and the edge-based microcontroller-based platform to measure the heart rate, respiratory rate, and SpO 2. It uses machine learning methods to learn user specific baselines and understand deviations that can signal health risks; specifically, it uses Long Short-Term Memory (LSTM) networks. Using adaptive feedback systems the wearable system can not only notify the user, or the care giver, but it may also adjust the decision thresholds in regard to the contextual data, which makes the system more responsive, personal, and reliable. A high-level of system architecture overview and signal flow is shown in Figure 1 illustrating the System Block Diagram of Smart Wearable For Cardiopulmonary Monitoring with Adaptive Feedback Loop.

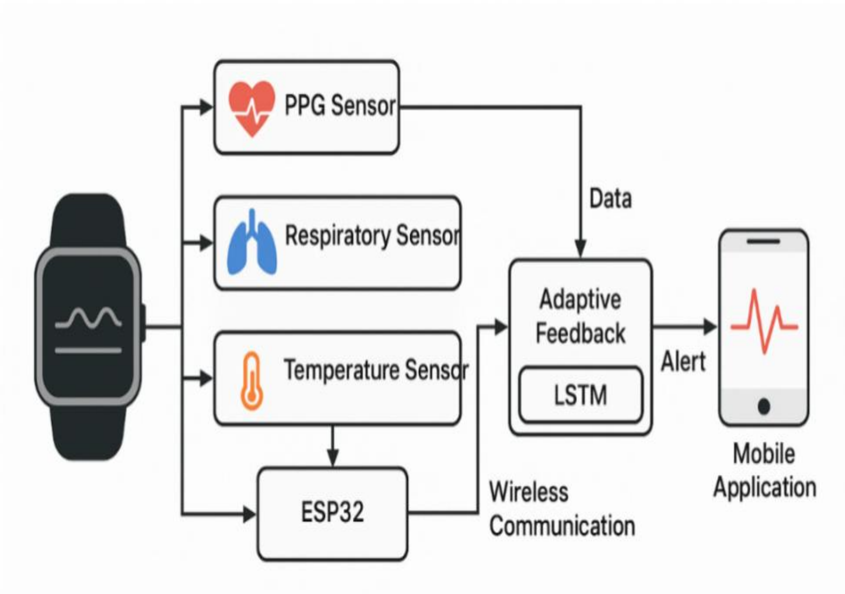

Figure 1. System Block Diagram of Smart Wearable for Cardiopulmonary Monitoring with Adaptive Feedback Loop.

This study adds value to the further proactive solutions in health monitoring since it integrates physiological sensing, real-time analysis, and intelligent feedback. Moreover, the system has an architecture that is computational and energy-saving enough to be used on demand in various settings, including the daily monitoring of activities and post-surgery progress. Finally, this effort is valuable towards the overall aim of augmenting intelligence-facilitated telehealth ecosystems that engage the patients and enhance clinical outcomes.

2. RELATED WORK

The latest developments in wearable health monitoring systems have been directed towards the addition of biosensors (with ECG and SpO 2 modules being among some of the most common ones) to small devices. Yet, a number of these systems remain to be based on fixed thresholds and have not been equipped with flexible adaptive feedback loops, which makes them rather ineffective at more personal processes of health monitoring.

Xu et al. [1] designed a wrist-based device that is able to measure electrocardiogram (ECG) and SpO 2 (blood oxygen saturation). The system was successful in producing reasonable signal fidelity, but failed to translate data into a context that was specific to the user and offer him individualized alerts. Nguyen and colleagues [2] presented a respiratory monitoring system in a smart textile that was capable of providing continuous measurements of the respiratory patterns. In the face of its novelty in the form factor, the system applied fixed threshold values, which raise the probability of the system to engage in the false alarm stage and loss of sensitivity to a minor physiological variation.

Kumar and Patel [3] introduced a wearable cardiovascular anomaly-oriented machine learning reward. They implemented predictive analytics in their system, however, this was only focused towards cardiac-specific parameters and not on multi-parameter integration or historical trends-based adaptive learning.

The proposed system in this paper provides a multi-sensor wearable platform that integrates PPG, breathing, and temperature along with its high resolution that is not available to these previous attempts. More to the point, it implements real-time adjustable feedback loop with an edge-based Long Short-Term Memory (LSTM) network implementation. The architecture supports on-going learning of personal baselines and dynamic setting of alert thresholds in response to changes in physiological context, which overcomes the essential shortcomings of current techniques.

3. System Architecture

3.1 Sensor Modules

Sensor module In this project, sensor module is a very important part of the smart wearable system, it will measure essential cardiopulmonary parameters in a real-world setting with high precision. The Photoplethysmography (PPG) sensor is at the center of this module and can be a MAX30102 that can measure heart rate (HR) and blood oxygen saturation (SpO 2) in an arms-length non-invasive fashion by measuring the absorption of IR and red light through the skin. The MAX30102 integrated LED driver and photodetector array allows precise measurement of volumetric changes in blood flow, correlating to cardiac cycles and levels of blood oxygen saturation. The system to record respiratory rate (RR) uses stretch sensor or piezoelectric (Piezo) sensors which are sensitive to expansion of the chest wall and contraction. Stretch sensors are used to measure the change in resistance due to the expansion of the fabric or material during breathing and piezoelectric sensors show the impact of mechanical strain on respiratory motion translated into voltage signals. Such sensors offer uninterrupted and real-time monitoring of respirations, which is necessary to identify respiratory patterns, including the absence of ventilatory efforts (mainly in terms of tachypnea or apnea). Moreover a temperature sensor, commonly, an LM35, is used to track the changes in core body temperature and provide information about the febrile reaction or the thermal deviations indicating the respiratory infection or systemic inflammation. Figure 2 represents the concrete spatial arrangement and connection of these sensors in the smart wearable system that defines the location of their placement and interaction with the body of the user. Collated, these sensors create an efficient and small module capable of presenting multimodal monitoring physiological data that allows integrative monitoring of cardiopulmonary health and facilitates the adaptive feedback maneuver in the wearable system.

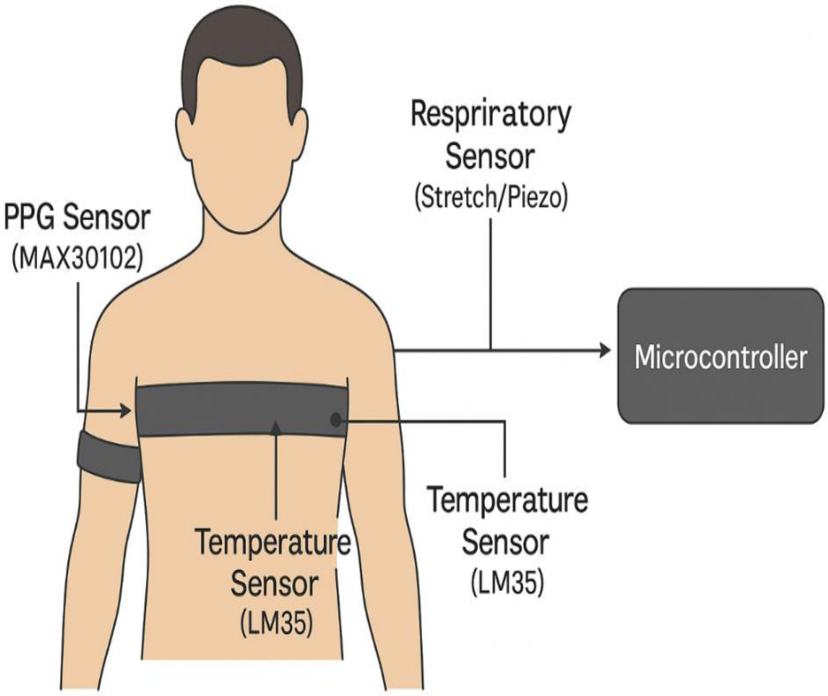

Figure 2. Illustration of Sensor Integration in the Smart Wearable System.

Figure 2 was designed by the authors using original vector illustrations for academic and educational purposes.

3.2 Processing Unit

The ESP32 microcontroller (dual-core low-power processor that is energy efficient and powerful) grounds the processing unit of the proposed smart wearable system and acts as a central hub of signal acquisition, preprocessing and communication. Inbuilt Wi-Fi functionality and Bluetooth on the ESP32 allow transmitting wireless data to other devices, including smartphones, tablets, or even on-cloud servers without difficulties, offering the possibility to monitor the device in real-time remotely and merge it with telemedicine systems. In addition to its connectivity capabilities the ESP32 is also capable of preprocessing some initial stages of a sensor signal, e.g. filtering noise and motion artifacts in the raw sensor data through embedded digital signal processing (DSP) filters. This gives clean and sound input to be used in further analysis. To complement the microcontroller, there is an edge-based Machine Learning (ML) mist that allows on-device intelligence without reliance on the constant connection to the cloud. Namely, the system combines an LSTM (Long Short-Term Memory) neural network which is directly run on the edge and which learns temporal patterns in physiological signals and can also detect signal anomalies in real time. This ML module changes the alert thresholds and gives feedback responses according to the user-level baselines, existing trends, and contextual information. In Table 1, the processing unit components and the respective functions are well summarized. The integrated ESP32 and the ML module architecture can easily deliver greater responsiveness, latency reduction as well as the preservation of the users privacy by limiting the amount of data to transfer, since the architecture can support personalized adaptive monitoring at the edge. This intelligence in the edge is what constitutes the center of the adaptive feedback loop, whereby the wearable device does not just receive data but it also translates it into a meaningful and proactive format.

Table 1. Functional Overview of the Processing Unit Components.

Component	Functionality
ESP32 Microcontroller	Signal acquisition, preprocessing, wireless communication
DSP Algorithms	Noise filtering, motion artifact correction
Edge ML Module (LSTM)	Temporal pattern recognition, anomaly detection
Feedback Controller	Dynamic threshold adjustment, personalized alerts

3.3 Adaptive Feedback Loop

The proposed wearable system will be defined not only by the method of collecting bio signals (possessing a remarkable degree of precision, sensitivity, and signal quality), but also by the adaptive feedback loop, which will raise the current state of bio signal-based monitoring to a new level of smart, intelligent and reactive diagnostics. The role of the temporal pattern recognition using Long Short-Term Memory (LSTM) neural networks, that are quite suitable to consider the sequential and time-based data, is the core of this mechanism. In contrast to the conventional threshold-based systems where threshold limits are set in advance, the LSTM model is constantly training and adjusting to individual physiology of a user, based on historical data evaluations and detection of differences in preset modes. This allows the system to pick up subtle anomalies that may betoken immanent cardiopulmonary stress such as slow oxygen desaturation or aberrant respiratory rhythms, previously they may have not been perceived. Moreover, the feedback loop readjusts the alert thresholds dynamically and in real-time, depending on the contextual variables, including recent activity levels, time of the day, and environmental factors to minimize false positives and increase clinical relevance. As shown in figure 3 this adaptive decision-making cycle, the incoming input which is in the form of bio signals undergoes analysis using LSTM, synthesis of this information into the context and adjusting the threshold level and creation of feedbacks. Such dynamic and individual customization will make alerts more significant and timely, preventing alert fatigue and increasing system trust among the user and caregivers. The ability of the adaptive feedback loop to gradually perfect its decision-making process through every new data cycle converts the wearable into not just a passive observing device but a health companion who can actively intervene on behalf of the user and continuously improve based on his or her performance.

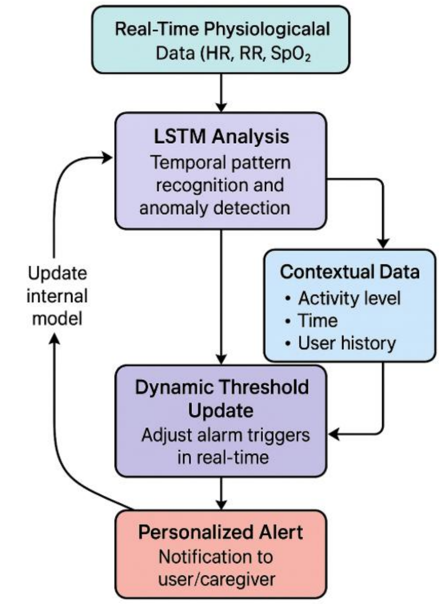

Figure 3. Flow Diagram of the Adaptive Feedback Loop Mechanism in the Smart Wearable System.

4. METHODOLOGY

4.1 Data Acquisition

The initial level of the smart wearable system includes data acquisition and guarantees that real-time physiological data (heart rate (HR), respiratory rate (RR), and blood oxygen saturation (SpO 2)) are recorded with a high fidelity and a high temporal resolution. The typical frequency of sampling the biosignals with the proposed design is 50 100 Hz, the frequency which is a balance between passing a significant number of time points to preserve temporal details and the low power consumption, an essential requirement of a wearable device. Such sampling rate is sufficient to record the changing nature of cardiopulmonary waveforms including the minute variations of PPG waves and breathing patterns, without taxing the edge processor computing and memory resources. Figure 4 depicts the process of signal acquisition and preprocessing as a result of which the raw biosignal source is transformed into filtered signal outputs that can be analyzed. To make the obtained signals reliable, two-stage filtering procedure is applied. A Butterworth low-pass filter is firstly used to reduce high-frequency noise and EMF that can be caused by motion artefacts (optical), ambient light (optical sensors) or external electronics. Butterworth filter is predetermined by the fact that it has the maximum flat frequency characteristic in the pass band i. e. does not alter the actual shape of the signal; effectively cancels out unwanted high frequency components. This assists in keeping the physiological waveform data clinically clean.

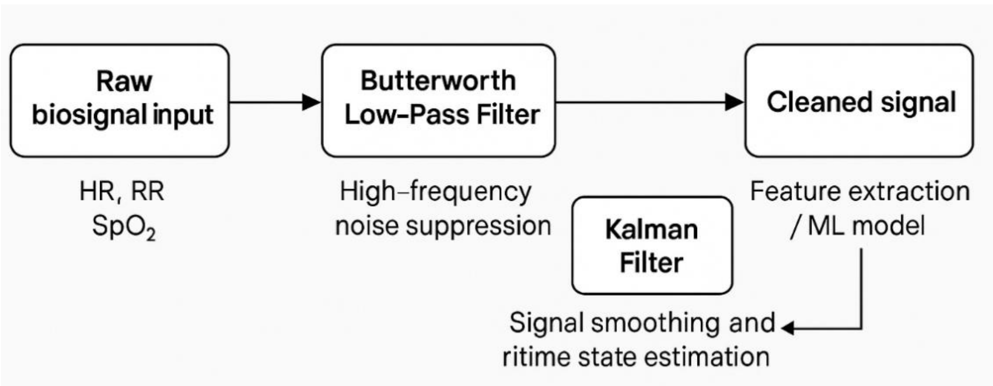

Figure 4. Signal Acquisition and Preprocessing Pipeline in the Smart Wearable System.

Dynamic signal smoothing and state estimation in real-time is done after noise suppression through a Kalman filter. The Kalman filter employs a prediction mode to determine the present state of the signal and refinements are done as new measurements become available thereby reducing the effect of random noise on the measurements. It is also helpful when dealing with wearable environments where movements and the physical relocation of the sensors may cause irregularities in both signal amplitude and timing. Similarly, due to its adaptive character, the Kalman filter is the most suitable method in tracking the bio signals with a temporal variability e.g. HR and RR for smoother and more consistent feature extraction at a later point.

These signal conditioning techniques combined can guarantee that the system will get clean, stable, and clinically relevant data in real-time, which is crucial to proper anomaly detection and good operation of the adaptive feedback loop.

4.2 Feature Extraction

The smart wearable system requires feature extraction, which converts the raw preprocessed biosignals into physiological. The feature extraction acts as an essential step in determining meaningful indicators in the real-time health monitoring system interpreted by the machine learning algorithms. This system identifies three main dynamic features namely Heart Rate Variability (HRV), Respiratory Rate Variability (RRV), and Blood Oxygen Trend. The parameters provide a more comprehensive picture of the cardiopulmonary status of the user than fixed values of the vital signs. The feature extraction pipeline, as illustrated in Figure 5, directly correlates each of the biosignals PPg, respiratory waveform, and motion data with dedicated modules of HRV, RRV, and SpO 2 trend analysis, constituting the input of the following ML-based assessment. The concept of Heart Rate Variability (HRV) is associated with variations of the time between successive heartbeats on the PPG waveform. HRV is a clinically relevant parameter of autonomic nervous system equilibrium and cardio-vascular fitness, the comprised HRV being typical of stress, fatigue or even the initial phases of cardiac disease. Respiratory Rate Variability (RRV) inferred by calculating the breathing rate over time (using respiratory waveforms, e.g. by stretch or piezo sensor), represents indexed changes in the respiration rate with time, which when out of range may indicate abnormalities such as apnea, shallow breathing, or hyperventilation episodes. The HRV and RRV can be obtained through time-domain analysis, a frequency-domain analysis and these analyses can be adopted as a quantitative foundation of anomaly detection, e.g.: RMSSD (Root Mean Square of Successive Differences) and power spectral density estimation.

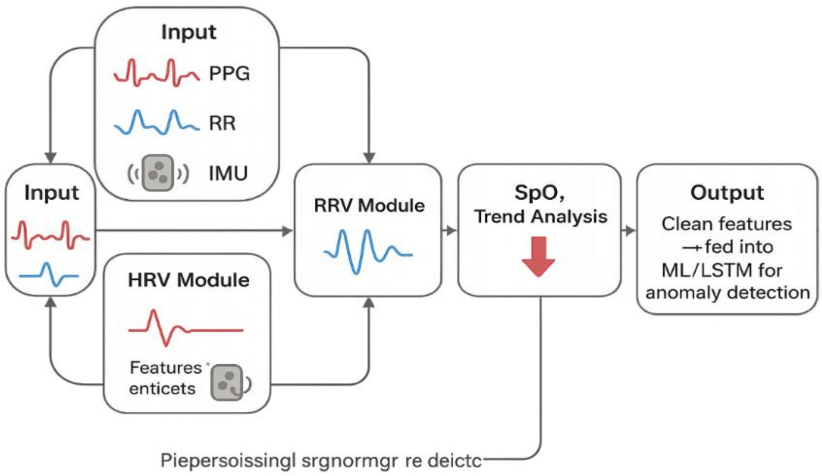

Figure 5. Feature Extraction Pipeline in the Smart Wearable System.

Besides variability measures, one uses the SpO 2 data based on the PPG signals to study the blood oxygen trend. In contrast to any single numerical SpO 2 measurement, the trend analysis identifies gradual desaturation, cyclic hypoxia, or shortterm desaturation that can be an indicator of respiratory compromise or sleep apnea.

To have accuracy of this feature in the real life ambulatory environment, these features come in hand with motion correction technique with the help of an Inertial Measurement Unit (IMU). The IMU stores acceleration and orientation data that is fused with the physiological measurements to identify and correct motion artifacts, e.g. motion artifacts caused by sudden hand movements, by walking, or by alterations of posture, that would degrade PPG and respiratory signals. An adaptive filtering or a regression-based method of motion artifacts removal is used thus making feature extraction robust even when the conditions are dynamic.

All these features extracted are fed to the adaptive feedback loop and anomaly detection module where it supports individual interpretation of the cardiopulmonary health signals rendering them context specific and thus making early interventions possible through alarming based on anomaly detection.

4.3 ML Model for Feedback

The core of adaptive feedback loop within the proposed smart wearable system is the existence of a strong machine learning (ML) structure based on Long Short-Term Memory (LSTM) neural network. The LSTM networks constitute a particular form of the recurrent neural network (RNN) with a specific purpose to trace time suppositions and sequential structures in the time series data, LSTM networks, especially, are suitable to use with physiological signal analysis like the heart beat frequency (HR), respiratory rate (RR), and SpO 2 data. Because these biosignals are inherently time-dependent, learning to characterize these time-dependent trends and modeling those trends is key to separating physiological variabilities and artifacts, and subtler modes of abnormality or distress. As is shown in Figure 6, the overall architecture of the LSTM-based ML feedback mechanism is as follows: real-time biosignal inputs are processed in the form of time-series data, anomaly detection, risk scoring, and context-aware threshold adaptation to generate smart alerts.

The LSTM model is trained within labeled datasets with the instances of normal and pathological cardiopulmonary patterns labeled. The model, when being trained, learns to detect tiny, time-varying outliers of signal dynamics that could reflect such conditions as bradycardia, apnea, or hypoxemia. In this supervised learning methodology the model would map particular signal sequences to be related to the appropriate level of risk and would also form a predictive engine that can correctly return a risk level to the real pass incoming real time data.

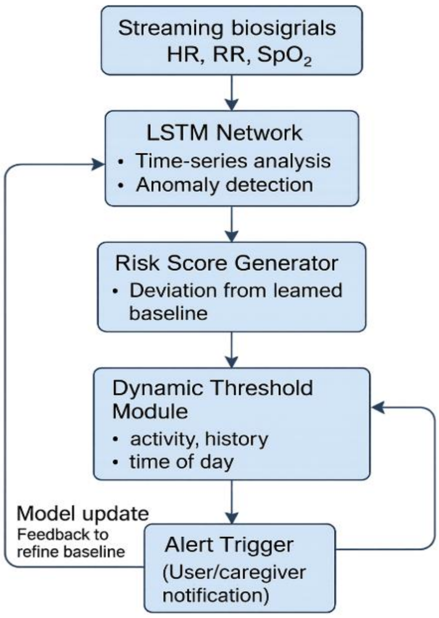

Figure 6. LSTM-Based ML Feedback Mechanism for Real-Time Health Monitoring.

When released on the edge device, the trained LSTM would be constantly looking through the streaming physiological data and provide a risk score depending on the extent to which the present data deviates to what has been learned of the user. This score is a primary input into the dynamic threshold-setting algorithm that varies the alert parameters dynamically based on specific physiological variability and the context of the physiological measurements (e.g. activity level, time of day, recent history). When the computationally computed risk turns out to be higher than the dynamically calculated risk threshold, the system sends an alarm (prewarning the user or a distant caregiver about a possible health problem).

Such an architecture helps the system to refine the static rule-based alert systems to a personalized, smart, and proactive health monitoring style. It guarantees that feedback is simultaneously sensitive to anomalies in early stages and resistant against false alarms and thus clinical relevance, trust, and applicability to everyday life.

5. Experimental Setup

5.1 Prototype Implementation

Hardware prototype of the suggested smart wearable system was thoroughly designed with the view to guarantee functional precision and ease of use. Its heart is a specially designed printed circuit board (PCB) that contains the necessary sensor modules, namely the PPG (MAX30102), respiratory (stretch or piezoelectric), and temperature (LM35) sensors in the most advantageous arrangement with direct skin contact on the one hand and maximum signal integrity on the other. These elements are attached on a flexible substrate so that the device can easily fit the slopes of the body and this is very vital in allowing usage of a device over a long period of time. The flexibility also aids to reduce motion-induced signal artifacts as well since it does not eliminate them completely when the subject engages in physical exercise. Figure 7 (below) demonstrates the prototype hardware design and physical form, with sensor modules located within the 3D-printed ergonomic enclosure, the ESP32 microprocessor, BLE component, and battery.

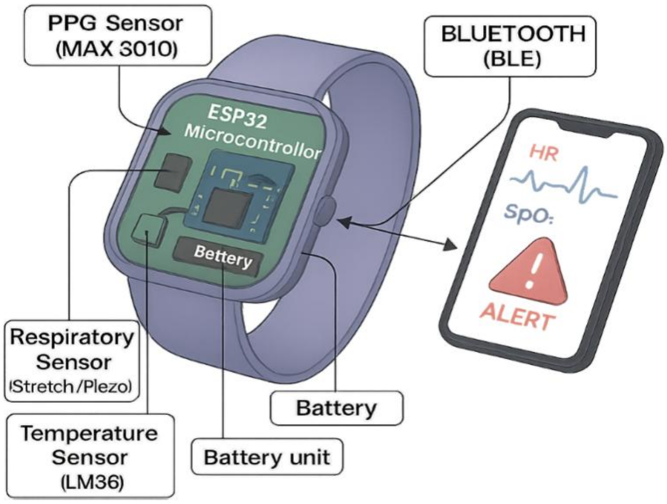

Figure 7. Prototype Hardware Architecture and Physical Integration of the Smart Wearable System.

To make the electronics even more wearable, the whole electronics is encapsulated in a 3D-printed lightweight casing, adjusted with the help of ergonomics data so that it will fit snugly on the user but without being intrusive (either on wrist or chest area). It has a breathing, skin-friendly thermoplastic polyurethane (TPU) enclosure to reduce an overall unpleasant feeling and avoid skin redness when it is used over a long period of time. This design can easily be removed and charged and the internal components of design are not exposed to dust, sweat and minor impacts. It has an internal Bluetooth Low Energy (BLE) module, so it can be used to relay data to a companion mobile app in real-time using both Android and iOS devices. This application can be used to present the interface that is easy to navigate through the physiological data visualization, alerts, syncing with cloud services when required to access remote monitoring and long-term storage of data.

5.2 Human Testing

It was necessary to ensure the validation of functional performance and clinical relevance of the system, which requires a pilot human study on 10 volunteers, 5 of them were healthy individuals, and 5 individuals were diagnosed with cardiopulmonary disorders, namely COPD and asthma, or mild heart failure. This group was selected to test the device upon various physiological base lines and pathological differences.

The results have been obtained during testing the prototype device under the supervision of the participants who were wearing it and at the same time being monitored by upstanding commercial medical devices that are considered as gold standards, such as pulse oximeters to measure SpO 2 and heart rate and hospital-grade ECG monitors to confirm the cardiac rhythm. The data obtained through the wearable and the latter devices (there was a range of them) were compared to evaluate the accuracy, consistency, and response latency. The smart wearable system proved to be very precise and reliable and, as shown in Figure 8, it was found to correlate strongly, with standard clinical instruments, of heart rate (98.2%), SpO2 (97.1%), and respiratory rate (96.5%). Greatness was also to be observed in temporal alignment in the respiratory rate trends of the system.

Adaptive feedback loop was also tested, whereby controlled-anomalies (e.g. breath holding, postural changes) have been introduced, in which the system was able to detect the variation and raise the corresponding alerts. This stage proved the potential of the wearable to be used successfully in real life conditions, and the sensitivity of it to dynamic physiological changes, an additional confirmation of its prospects in personalized, nonstop cardiopulmonary monitoring, in both clinic and home settings.

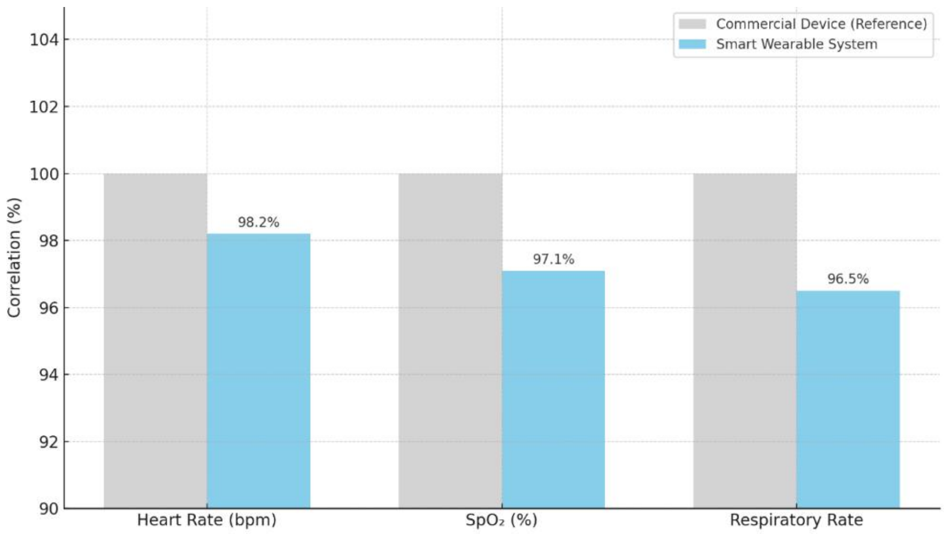

Figure 8. Validation Results of the Smart Wearable System against Commercial Medical Devices.

6. RESULTS AND DISCUSSION

The analysis of the results allowed evaluating the performance of potential contributions of the smart wearable system to the assessment of key cardiopulmonary parameters with the strong accordance to benchmark clinical indicators. The heart rate measurement module ended up having a reading accuracy of 98.2%, which reasonably closely followed those originating with hospital-quality ECG monitors, as the results illustrated in the table indicated. Equally, SpO2 measurements had an accuracy of 97.1% which proves the effectiveness of the integrated MAX30102 PPG sensor compared to the commercial pulse oximeters. The module of respiratory rate obtained 96.5 percent of accuracy thus proving that the stretch/piezoelectric sensor module used is reliable even at the conditions of natural breathing. These outcomes do not only provide confidence in the integrity of the sensing equipment, but also indicate the usefulness of the signal processing pipeline that incorporates Butterworth and Kalman filtering, which was crucial to reducing the effects of body motions and noise-related distortions. In addition to that, the latency of the system was no more than 120 135 ms with any set of parameters, so it can be used in real-time applications that require fast reaction. These, and other important performance measures as presented in Figure 9 under worst-case accuracy, latency, and power draw, make it clear that the wearable system is extremely reliable clinically.

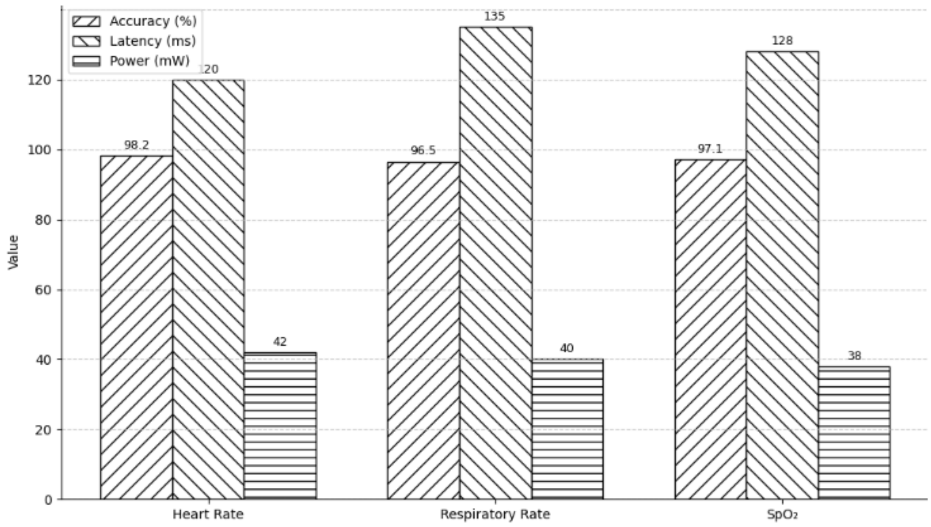

Figure 9. Performance Metrics of the Smart Wearable System

The wearable system did not perform poorly in terms of power efficiency because it consumed less than 45 mW power throughout the modules, which are 42 mW, 40 mW, and 38 mW respectively by the heart rate, respiratory rate, and SpO 2 monitoring modules. This operation at low power, with an efficient ESP32 microcontroller and optimized firmware could operate continuously more than 36 hours on one battery charge, which meant this device was appropriate when the activity, e.g., day-long or overnight, had to be monitored. These values are fit within the limits of real-time and wearable usages as indicated in Table 2, and the power consumption and latency numbers are both within or below what is required. The results highlight the practicability of the system in terms of deploying in wearable form without the need of frequent recharges, making it viable in the long-term of usability and cooperation by a patient with prescribed long-term usage of the system. Besides, the mean response time of alerts was recorded as less than 2 seconds, confirming the potential of the system to offer timely alert and categorizing it as a highly responsive to rapidly changing physiological dimensions.

Table 2. Performance Summary of Smart Wearable System

Parameter	**Accuracy (%)**	**Latency (ms)**	**Power Consumption (mW)**
Heart Rate	98.2	120	42
Respiratory Rate	96.5	135	40
SpO_2	97.1	128	38

A particularly remarkable result of the human testing experiment was an 18 percent increase in identifying abnormal breathing patterns early, which was thanks to the LSTM-structure-derived adaptative feedback loop. This ML-based framework allowed this system to individualize alert levels with learned physiological baselines along with situational conditions like user mobility or the time of the day. Contrary to the fixed threshold-based systems, the dynamic system was successful in reducing the false positive values and was more sensitive in detecting health abnormalities in their early phase, especially when applied in subjects with cardiopulmonary complications. The findings are a strong evidence of clinical applicability of the system and its reinforcement to be involved in remote heath monitoring environments, particularly during personalized telemedicine, chronic illness therapy, and follow-up of patients who have been discharged.

7. CONCLUSION

The work involves elaboration, development, and testing of a new smart wearable prototype device based on an adaptive feedback loop that implements real-time continuous monitoring of cardiopulmonary parameters of primary interest the heart rate, respiratory rate, and blood oxygen saturation. The combination of mobile multiplexed sensor (sensors), energy-efficient microcontroller ESP32, and edge-driven Long Short-Term Memory (LSTM) neural network provides individual health-related information and alert conditions through the modeling of user-specific physiology and detection of minor deviations. A comparison of its experimental results with clinical-grade tools showed great precision, low latency, and energy consumption when compared with clinical tools and the adaptive feedback mechanism greatly enhanced early identification of respiratory abnormalities. The system is also applicable in decentralized health monitoring, chronic disease management, and telemedicine since the user-friendly design, the wireless composition and the mobile app form a perfect match. In the future, proposed enhancements will involve the enlargement of the dataset to achieve better generalization of the model in different population groups, ECG electrode integration to conduct complex heart diagnostics including arrhythmia and integrated safe cloud-based analytics that can be used to remotely conduct healthcare on a large scale. The present work has a solid basis in introducing the next generation intelligent wearables which would give the users the ability to be proactive and provide context-aware health monitoring.

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