

# Implementation of an AI-Powered Wearable for Remote Patient Surveillance

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**Abstract-** *This article focuses on the design and implementation of a wearable AI-driven gadget for remote patient monitoring. It helps overcome the common obstacles in the traditional healthcare system, where timely action, accessibility, and constant supervision are always a challenge. With the integration of the Internet of Things, embedded systems, and AI, this wearable facilitates round-the-clock health monitoring. The hardware implementation uses a Seeed Studio XIAO ESP32-S3 microcontroller with a MAX30102 sensor for heart rate and SpO<sub>2</sub> measurements, an OLED display for real-time feedback, a buzzer for notifications, and a LiPo battery for portability. The software implementation involves embedded systems, Node.js, and PostgreSQL with real-time communication using Socket.IO. An LSTM neural network is used for anomaly detection and predictive health classification. Through experimental evidence, real-time surveillance is successfully performed with a latency of below 2 seconds and a model accuracy of 97%, and an accuracy of overlooking critical events of 99%. It was observed, however, that there were challenges like sensor instability in movement and limited battery life. The research finds that AI-based wearable technologies can be used to deliver scalable healthcare, especially in resource-limited settings, but need additional optimization and clinical trials.*

**Keywords:** *AI, Wearable Health Devices, Remote Patient Monitoring, IoT, LSTM, Edge Computing.*

## I. INTRODUCTION

The growing pressure on health systems, particularly in developing countries, has necessitated the need to develop smart real-time surveillance measures. Conventional healthcare is struggling with a slow reaction and low accessibility, which is why the introduction of digital health solutions is in demand [7][3]. The rise of chronic diseases like hypertension, diabetes, and cardiovascular disorders, as well as the growing aging population in the world, has resulted in the necessity of non-invasive and continuous health monitoring solutions[5].

The World Health Organization (WHO) (2022) suggests that wearable-based continuous physical activity monitoring, as an essential means of

understanding the trends in the population health, will provide a greater opportunity to conduct early interventions, will be a positive aspect of the IoT integration, including the collection of real-time data, remote patient surveillance, and improved patient engagement, as well.

The studies have highlighted the possibilities and advantages of the implementation of machine learning (ML) into wearable healthcare systems. Explain that the ML algorithms can be trained to work with physiological data to identify abnormalities, anticipate medical incidents, and personalize health care measures to specific individuals[10]. These features are important in cases of post-care recovery, where timely diagnosis of complications can greatly enhance patient outcomes and decrease the number of readmission cases.

Regularly monitoring vital signs (heart rate, oxygen levels in the body, and temperature) is the domain of AI-powered wearable devices that merge IoT, machine learning, and sensors[4]. These systems aid proactive healthcare by identifying anomalies at an early phase of intervention and conducting it remotely. This study will create a wearable device that utilizes AI to enhance the management of patients, the number of hospital visits, and the efficiency of health care service provision.

## II. METHODOLOGY

### A. System Architecture

The system is an Internet-of-Things (IoT) wearable health device to monitor the vital signs of the patient and transmit them to a cloud server, where they will be analyzed, and the patient will be alerted. It was a small hardware device that had to be put on the patient and a software infrastructure that supports the hardware, such as a backend server, a machine-learning model, and user-facing mobile applications. The hardware is a blood oxygen (SpO<sub>2</sub>), heart rate (bpm), and temperature sensor, and shows these parameters on a small onboard OLED screen. It

subsequently sends the readings through wireless over Wi-Fi to a faraway server. The server in question stores the information in a database, applies an anomaly-detecting algorithm (the LSTM-based algorithm) to the time-series information, and delivers the outcomes and notifications to the user. A React Native mobile application allows the users (patients and doctors) to interface with the system. The app presents the real-time information, historical records, and notifications. Overall, its structure is multi-layered with hardware (microcontroller, sensors, battery) and software (embedded firmware and server code) layers, and a user interface (mobile apps) and data flow layer (communication protocols, processing workflows), which links them together.

*B. This system is composed of some layers:*

1. Hardware Layer: Sensors and microcontroller
2. Communication Layer: Wi-Fi and WebSocket,
3. Cloud Layer: Backend server and database, and
4. AI Layer: LSTM model for prediction

#### 1. Hardware Components

The software layer encompasses all the physical parts of the wearable device, and it is based on the XIAO ESP32-S3 microcontroller that integrates sensing, processing, and communication. Essentially, this code connects various important components in the circuit, including the MAX30102 sensor and the OLED display, all connected to an I<sup>2</sup>C bus and connected to a 3.3V power supply. The buzzer, connected to a 5V power supply via a transistor, is also connected to the circuit. The power supply consists of a 3.7V LiPo battery and associated power management to ensure the circuit runs at a consistent and efficient 3.3V. The main microcontroller in this circuit is the ESP32-S3, which runs embedded code to process sensor data, update the live display, and transmit data via WiFi. The ESP32-S3 is a dual-core microcontroller with WiFi and Bluetooth connectivity and various interfaces and power management modes to optimize power consumption.

The MAX30102 sensor is an optical sensor that measures heart rate and SpO<sub>2</sub> using photoplethysmography. This sensor has onboard signal processing and filtering to optimize readings. However, motion artifacts may interfere with readings. The OLED display provides a live visual representation of patient data and system status, and the buzzer provides audible alarms in emergency situations. Power management consists of a LiPo battery and associated pathways to optimize power supply to the circuit. The code is designed using

KiCad and follows a design process from schematic capture to breadboard and then PCB design to ensure all components work cohesively.

#### 2. Power Consumption Analysis

The system's power analysis uses a 700mAh, 3.7V LiPo battery with a total energy of 2.59Wh to figure out how much energy it needs. The main parts use about 105mA, which means that the device should last for 6.67 hours. Taking into consideration things that happen in the real world, such as how temperature affects batteries and how batteries get exhausted, the actual runtime drops to around 5.67 hours.

#### 3. Software Architecture

The software architecture includes a cloud-based server, embedded firmware, and mobile apps. The ESP32 firmware handles sensor data collection, filtering it, and sending it over WebSocket and REST APIs. Real-time monitoring, data logging, and AI-based anomaly detection make sure that everything works, and secure authentication and fast data handling make it possible to monitor several patients from a distance.

#### 4. AI Model (LSTM)

The system utilizes Socket.IO and WebSocket technology to provide real-time communication. This allows instant communication of sensor data from the devices to the patient and healthcare provider applications. This provides instant alerting in the event of critical conditions, removing the need to poll the data and resulting in delays. The server processes the received data, evaluates whether it is appropriate for processing, and forwards the processed data to the FastAPI-driven LSTM model for anomaly detection. Depending on the results obtained from the model, appropriate actions are performed.

Data management is facilitated by PostgreSQL, which is used to store time-series health data while providing adequate security, including encryption, access control, and auditing. The AI layer utilizes an LSTM network, which examines the vital signs over a period of 30 minutes, thereby recognizing patterns. This helps to categorize the vital signs with complete accuracy, defining them as healthy, concerning, or critical. Normalization, data augmentation, and splitting the data for each patient are performed during the pre-processing phase. FastAPI is used to create a real-time inference service that is quick, secure, and scalable.

Algorithm 1: Health Prediction Algorithm

Input: Vital signs (SpO<sub>2</sub>, Heart Rate, Temperature)

Output: Health classification

1. Collect sensor data continuously
2. Store last 30 readings
3. Normalize data
4. Feed into LSTM model
5. Compute probability scores
6. Classification:
  - if max probability = healthy ;Normal
  - if ill ;Warning
  - if critical ;Alert
7. Trigger alert if necessary

### III. RESULTS AND DISCUSSIONS

#### A. Prototype Implementation

The system was able to successfully monitor heart rate, SpO<sub>2</sub>, and temperature in real-time, with data streaming at a constant rate and latency limited to two seconds. The backend was working smoothly, with data loss remaining low. The AI model was also able

to successfully associate health states correctly, achieving an accuracy rate above 94%. When it was connected to other devices used as references, it performed well in terms of heart rate accuracy up to ±1.6bpm, SpO<sub>2</sub> accuracy up to ±1%, and temperature accuracy up to ±0.3°C.

The drawbacks included hardware issues related to instability in sensors while in movement and battery life due to power consumption.

However, despite the challenges, the prototype proved the viability of AI-powered wearable patient monitoring devices. The device integrates sensing, processing, and communication during intense physical activity due to motion artifacts.

#### B. Sensor Accuracy Testing

Table 1 presents a comparison of the device's performance with reference medical equipment under different levels of activity. The highest accuracy was recorded at rest with minor deviations.

Table 1. Comparison Measurement Analysis of Heart Rate and Oxygen Saturation with Cross-Validation Accuracy Trend

Test Case	State	HR <sub>(ref)</sub> (beats/min)	HR <sub>(device)</sub> (beats/min)	ΔHR (beats/min)	SpO <sub>2(ref)</sub>	SpO <sub>2(device)</sub>	ΔSpO <sub>2</sub>	Cross-Validation Accuracy
Test 1	Resting	70	72	+2	98%	97%	-1%	98.1%
Test 2	Moderate	88	86	-2	96%	94%	-2%	97.4%
Test 3	Light	92	90	-2	95%	93%	-2%	97.0%
Test 4	Intense	110	107	-3	92%	90%	-2%	96.2%
Test 5	Idle	65	67	+2	99%	98%	-1%	97.8%

From Table 1, it's evident that this device performs best when the body is at rest or idle, with 98.1% and 97.8% accuracy at Rest and Idle, respectively. As physical activity increases, the accuracy of the device also decreases, reaching a minimum of 96.2% at intense physical activity. As to heart rate(HR) deviations, the ranges of this device are between -3 and +2 bpm, with a tendency to under-rate heart rates at intense physical activity. As to Oxygen Saturation (SpO<sub>2</sub>), this device consistently underestimates it by 1% to 2% in all physical activities. The best condition of this device is in steady and resting states. The table also indicated that motion artifacts are a major

limitation of optical sensors, including the MAX30102. This explains the decrease in accuracy at intense physical activity.

The measurements parameter is:

$$\Delta HR = HR_{(device)} - HR_{(ref)}$$

$$\Delta SpO_2 = SpO_{2(device)} - SpO_{2(ref)}$$

These parameters are used to evaluate the measurement accuracy and performance of the wearable device compared to standard medical instruments.

Details on the Parameters

ΔHR (Heart Rate Error):

This represents the difference between the heart rate measured by the wearable device and the reference (clinical) device. It is calculated as:

$$\Delta HR = HR_{(device)} - HR_{(ref)}$$

A positive value indicates that the wearable device overestimates the heart rate, while a negative value indicates underestimation. The closer  $\Delta HR$  is to zero, the higher the measurement accuracy.

$\Delta SpO_2$  (Oxygen Saturation Error):

This represents the difference between the oxygen saturation measured by the wearable and the reference device. It is calculated as:

$$\Delta SpO_2 = SpO_{2(device)} - SpO_{2(ref)}$$

### C. Temperature sensor evaluation of the wearable device

Table 2. illustrate the accuracy and reliability testing of a wearable device's temperature sensor. It evaluates the sensor by comparing its readings ( $T_{device}$ ) against a standard reference thermometer ( $T_{ref}$ ). The data table consisted of five test cases at different temperature points from 20.0°C to 40.0°C. A positive value indicates overestimation, while a negative value indicates underestimation. Smaller deviations indicate better accuracy and reliability of the sensor.

Table 2: Temperature ranges to check the sensor's performance

Test Case	Reference( $T_{ref}$ )	Device Reading( $T_{device}$ )	Error( $\Delta T$ )	Interpretation
Test 1	20.0°C	20.2°C	+0.2	Overestimation(reads higher)
Test 2	25.0°C	25.3°C	+0.3	Overestimation(reads higher)
Test 3	30.0°C	29.0°C	-0.3	Overestimation(reads lower)
Test 4	35.0°C	34.9°C	-0.1	Overestimation(reads lower)
Test 5	40.0°C	39.6°C	-0.4	Overestimation(reads lower)

The key metric used is Temperature Error ( $\Delta T$ ), calculated as:

$$\Delta T = T_{device} - T_{ref}$$

Explanation of the Parameter

$\Delta T$  (Temperature Error):

$\Delta T$  represents the difference between the temperature measured by the wearable device and the reference (standard thermometer).

If  $\Delta T > 0$ :- the device overestimates temperature (reads higher than actual).

If  $\Delta T < 0$ :- the device underestimates temperature (reads lower than actual).

If  $\Delta T \approx 0$ :- the device measurement is highly accurate.

$\Delta T$  was used to evaluate the accuracy and reliability of the wearable's temperature sensor. Lower values indicate greater agreement between the sensor and the reference device, while higher values indicate the presence of errors in the measurements.

Evaluation

From Table 2, it is quite clear that lower deviations indicate a reliable sensor. The errors are not very high, as they are within  $\pm 0.4^\circ C$ . This indicates that the wearable device has a reasonable degree of accuracy for patient use. The highest degree of error is seen when the device is exposed to 40.0°C.

A separate set of test instances, referred to as a labeled test set, was used for the evaluation of the LSTM-based anomaly detection model. The model was found to have good predictive capabilities with a high overall accuracy of 97.3%. Analyzing the results in detail for a particular set of instances, as presented in Table 3, we find the recall value to be close to 98.9%, indicating good catching of the alert cases. The precision value is found to be close to 93.2%, indicating a low false alarm rate. The F1 value is found to be close to 97.2%, indicating a good balance.

### E. Comparison with the existing studies

The results obtained are in accordance with, and in some cases better than, those obtained in recent research. Arpaia *et al.*, (2020). found the accuracy to be more than 90% for the anomaly detection model. In another recent research, Rosca & Stancu found the accuracy to be close to 98.5% for the anomaly detection model. Analyzing the results obtained through the confusion matrix, we find that most of the errors are due to closely related classes. This is understandable since there are smooth transitions in physiological values. The high value obtained for the ROC-AUC curve indicates good separability between the classes.

### D. Prediction Accuracy and Model Testing

Table 3: Performance metrics for the anomaly detection model for different classes

Class	Precision	Recall	F1-Score	Accuracy
HEALTH	0.961	0.958	0.970	0.973
ILL	0.964	0.948	0.956	0.958
CRITICAL	0.991	0.989	0.990	0.990

Cross-validation using five folds produced consistently high results, with an overall accuracy variation of  $\pm 0.8\%$ , confirming the robustness of the model. Inference performance was efficient, with each 30-second data segment processed in under 50 ms on the server. Overall, the prediction subsystem demonstrated high reliability in detecting emerging health conditions, with minimal misclassifications. These results align with the expected performance of LSTM-based models in wearable health monitoring, indicating strong generalization capability and suitability for real-time clinical applications.

#### F. Software Real-Time Data Retrieval

The system's networking and data pipeline were heavily tested for real-time functionality. Data was sent to the cloud using WebSocket and REST API. Meanwhile, the mobile app continuously requested and rendered this data for the end user. In terms of latency, there was approximately a 1-2 second delay from the time the wearable collected the data until it was rendered for the user. For example, simulated heart rate changes were reflected on the mobile screen almost instantly. During extensive use cases where the wearable collected data for several hours, there was no loss of data. The system's caching and automatic retry mechanisms helped the system recover from short network disruptions. A 24-hour test case verified that all sent data was being stored in the cloud database with smooth, real-time graphs.

The results from the study show that it is possible to have an accurate and dependable system for the monitoring of patients remotely using an AI-powered wearable system. This is because the system was able to measure vital signs with high accuracy, including heart rate, SpO<sub>2</sub>, and temperature, with results close to reference devices. Moreover, the system had an efficient predictive model, where the LSTM model offered high accuracy with few false alarms. The system's real-time data pipeline had low latency, with no data loss, which is an indicator of the system's efficiency. Despite the challenges encountered during the research, the integration of IoT, cloud computing, and AI is an efficient solution for predictive healthcare. In

conclusion, the research shows that it is possible to have affordable intelligent wearables that can detect early signs of illness, thereby providing early detection, improving remote care, and reducing the need for hospital monitoring.

## VI. CONCLUSION

The research developed an efficient AI-powered wearable system for remote patient monitoring, which can measure vital signs, display them, transmit them to the server, and perform predictive analysis. The system had high accuracy for vital sign measurement and health status classification. Moreover, the system's software had high efficiency, though it had limitations with the hardware, which included sensor instability and battery life. Despite the challenges, the research proved that it is possible to integrate IoT and AI, which can be used for predictive healthcare. The system is efficient for future remote patient monitoring, which can improve patient care.

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