Comprehensive Home Monitoring System for Cardiovascular Health Management

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Abstract. Monitoring devices and systems are indispensable tools for patients with cardiovascular health issues. These tools are typically operated by trained personnel in healthcare institutions. However, the need to monitor patients' vital signs at home remains a significant challenge. To address this, we propose the design of a non-invasive, autonomous IoT (Internet of Things.) device capable of recording heart rate, blood oxygen levels, and body temperature. The proposed device integrates with monitoring and data control platforms using IoT protocols. For validation, the data collected by the proposed device was compared with that of a smartwatch using statistical methods based on mean, median, and mode determination. The prototype demonstrated results comparable to those of a smartwatch, with measurements of 77.49 bpm (heart rate), 98.79% (S_pO_2), and 37.37 °C (body temperature). In contrast, the smartwatch recorded 75.38 bpm, 98%, and 37.4 °C, respectively. The proposed predictive model serves as an analytical framework for the study variables, consisting of three layers that can be adapted to wearable monitoring devices with the proposed architecture. The model achieved an RMSE of 0.470 for blood oxygen, 5.769 for heart rate, and 1.534 for body temperature. The developed algorithm is intelligent enough to provide accurate predictions, helping to prevent major cardiovascular health complications in patients.

Keywords: IoT device · cardiovascular health · machine learning · SPO2

1 Introduction

Cardiovascular diseases are one of the leading causes of morbidity and mortality worldwide. According to statistics from the OPS[1], 2 million people died from cardiovascular diseases inhad elevated blood pressure without a diagnosis, the year 2019 [1].

[1] Pan American Health Organization.

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According to a STEPS survey conducted by the MSP[2] and the INEC[3] in 2018, data on cardiovascular health among individuals aged 18 to 69 years revealed that 45.2% had elevated blood pressure without a diagnosis, 12.6% had elevated blood pressure with a diagnosis but without any treatment, 16.2% had diagnosed hypertension with treatment but remained uncontrolled, and 26% had elevated blood pressure with treatment and was controlled [2].

Despite technological advances, there are still limitations in access to continuous medical care and the early detection of health problems. The current health monitoring system, especially for patients with chronic diseases or at risk, presents significant limitations that affect the quality of medical care, ranging from appointment scheduling to the shortage of human resources in the healthcare sector [3].

Among the limitations, we find that medical visits and laboratory tests are conducted infrequently, and access to specialized medical care, particularly cardiology, is restricted for some patients, especially those with reduced mobility. Likewise, healthcare professionals do not always have access to up-to-date patient data, making it difficult to make informed treatment decisions [4].

Therefore, the main objective of this project is to develop a technological solution aimed at individuals with cardiovascular diseases, in order to monitor their vital signs in real time using low-cost technology and the integration of IoT protocols. The study variables considered in this proposal are heart rate, blood oxygen level, and body temperature.

To complement the proposal, a model based on recurrent neural networks (RNN) is proposed. This approach allows for the analysis of sequential data, facilitating the learning of the behavior of the study variables, and, of course, enabling timely prediction of abnormalities [5]. This enables early assistance, improving the response capability in critical patient situations.

This document is structured as follows: Sect. 2 describes related work focused on continuous monitoring and machine learning techniques; Sect. 3 describes the materials and methods used, which are based on an IoT-based technological architecture; Sect. 4 presents the results and discussion. Finally, Sect. 5 concludes the study.

2 Related Work

In [6], a device is presented for measuring blood oxygen levels non-invasively, using the MAX30100 sensor and an Arduino Uno microcontroller. The device includes an alarm that is triggered when oxygen levels drop below 95%, making it a valuable tool for health monitoring. Additionally, it integrates an alarm to alert the user when S_pO_2 levels are below normal, allowing for quick intervention in case of hypoxemia. Furthermore, the device features an LCD screen that clearly and simply displays the S_pO_2 Omeasurement results. The tests conducted

[2] Ministry of Health.
[3] National Institute of Statistics and Censuses.

showed that the device's measurements are comparable to those of calibrated tools, with a mean error of only 0.0123%.

In [7], a home telemedicine system is presented, which involves the remote monitoring of patients. The system uses IoT devices and the cloud to securely and efficiently collect, analyze, and share health data. Users wear an affordable wristband that measures their heart rate and oxygen saturation. This data is transmitted via Bluetooth to a mobile application running on an Android TV. The application sends the data to the cloud, where it is analyzed by healthcare professionals. Based on the data analysis, professionals can issue medical prescriptions that are sent to the user through the app. The system also provides professionals with tools to track the patient's progress and manage their healthcare. A survey conducted with healthcare professionals yielded positive results. The majority of respondents (88.5%) expressed their willingness to implement the system in their practice, recognizing the importance of the collected data (92.4%) and the usefulness of the system's tools for medical care (76.9%).

In [8], a proposal is presented for the development of a monitoring system, which is specifically designed for the care of patients at home, providing a compact and affordable solution that offers timely medical information. The system has been designed with the perspective of incorporating cloud computing and IoT technologies in the future, enabling remote monitoring of the patient's data. The article describes in detail the design and implementation of the system's main board, the selection of biomedical sensors, the creation of the supports, and the programming of the system.

In their research work [9], an automated monitoring system is presented to ensure remote access and efficient data capture. This research used both qualitative and quantitative approaches. User tests were conducted to gather feedback on the proposed interface, and a comparative method was employed to assess the system's effectiveness in comparison to equipment available on the market. The information transmission phase sends data obtained from the sensors to the ThingSpeak IoT platform, while simultaneously using a local area connection through the VNC Viewer platform to ensure dual communication in case the ThingSpeak servers fail. Although the proposed system can measure basic parameters such as heart rate, temperature, and electrocardiogram (ECG), it is not suitable for providing definitive medical analysis. However, it is useful for obtaining basic data in educational settings, such as at the Instituto Superior Tecnológico Luis Tello in the province of Esmeraldas, Ecuador.

This article [10] presents a system based on Long Short-Term Memory (LSTM) neural networks for the detection and classification of cardiac arrhythmias. LSTM networks are a variant of recurrent neural networks (RNNs) that allow for the analysis of data sequences of variable length, making them particularly useful for processing temporal signals such as electrocardiograms (ECG). The proposed system uses an LSTM network to classify ECG signals as normal or with arrhythmias, based on prior training with labeled data.

In [11], a portable device is proposed that detects arrhythmias. The methodology is based on developing a simplified Convolutional Neural Network (CNN)

classifier capable of identifying multiple types of arrhythmias using real-time two-dimensional images of ECG waves. The proposed model achieves an accuracy of 99.23%, outperforming most existing solutions and demonstrating its potential for low-power portable devices.

Despite advances in IoT technologies, their implementation in healthcare faces challenges that limit their integration, especially in the design of portable devices for continuous monitoring of vital signs. One of the main challenges is ensuring the reliability in measuring parameters such as heart rate, blood oxygen levels, and body temperature, which are interrelated variables [12].

In addition, it is essential to maintain low energy consumption and continuous communication of health-related devices. To achieve this, it is necessary to integrate IoT technologies with lighter connection protocols, such as MQTT servers, which ensure continuous real-time data transmission and monitoring [13].

3 Materials and Methods

The technological proposal presented is aimed at patients with cardiovascular diseases, whether in hospital, clinical, or home settings. This is achieved through the development of a portable IoT device designed to facilitate continuous and non-invasive monitoring of vital signs. To carry out this proposal, a phase-based model has been designed [14], following the technological architecture proposed in Fig. 1.

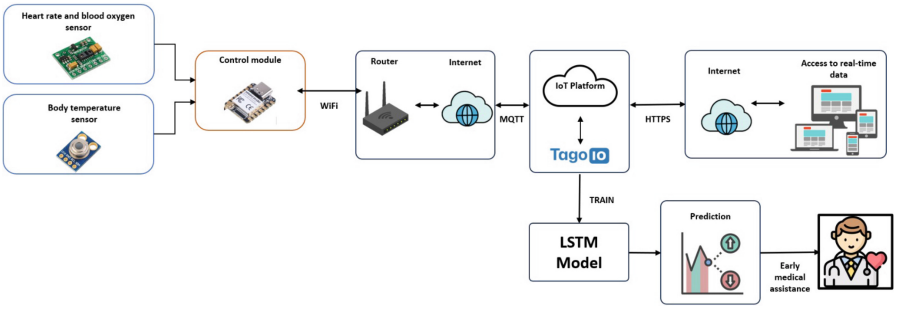

Fig. 1. Technological architecture.

The first phase consists of developing the IoT-based electronic prototype by integrating open-source hardware and software components. The component selection is primarily based on their dimensions, as the proposed device is designed to be portable.

The second phase focuses on collecting heart rate and blood oxygen level data using the MAX30100 sensor, with values recorded in beats per minute (bpm) and percentages (%), respectively. For measuring body temperature in degrees Celsius (°C), the MLX90614 sensor was used. The main control unit is

the Xiao ESP32C3 development board, chosen for being a microcontroller that supports low-power IoT communication protocols. The connection diagram of the proposal is shown in Fig. 2.

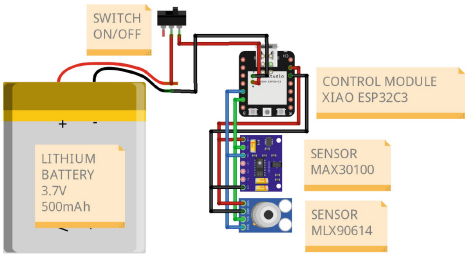

Fig. 2. Electronic diagram of the proposed components.

The third phase focuses on the design and 3D printing of a casing intended to integrate the electronic components in a way that makes the device compact, ergonomic, and non-invasive for the patient. Considering non-invasive aspects is important, especially for devices that require constant use, as it promotes user acceptance and satisfaction, increasing the likelihood of continuous use [15]. The dimensions of the casing are shown in Fig. 3.

The fourth phase focuses on validating the data collected by the proposed device, which are compared with data from a smartwatch. For the validation, the Xiaomi S1 Pro smartwatch was chosen, as it complies with European Union (EU) standards [16]. By applying statistical methods such as calculating the mean, median, and mode, an error margin is obtained. Below are the equations that define the mean (1), median (2), and mode (3) for heart rate, blood oxygen level, and body temperature.

$$\bar{FC} = \frac{\sum_{i=1}^{n} X_i}{n_{\text{val}}} \tag{1}$$

where:

- $\bar{X}$ represents the mean of the variable.
- X_i represents all recorded values of the variable.
- n_{val} is the number of non-null values of the variable.

$$\tilde{X} = \begin{cases} X_{\frac{n+1}{2}}, & \text{if } n \text{ it is odd} \\ \frac{X_{\frac{n}{2}} + X_{\frac{n}{2}+1}}{2}, & \text{if } n \text{ is even} \end{cases} \tag{2}$$

where:

- $\tilde{X}$ represents the median of the variable.
- X_i represents the recorded values of the variable.

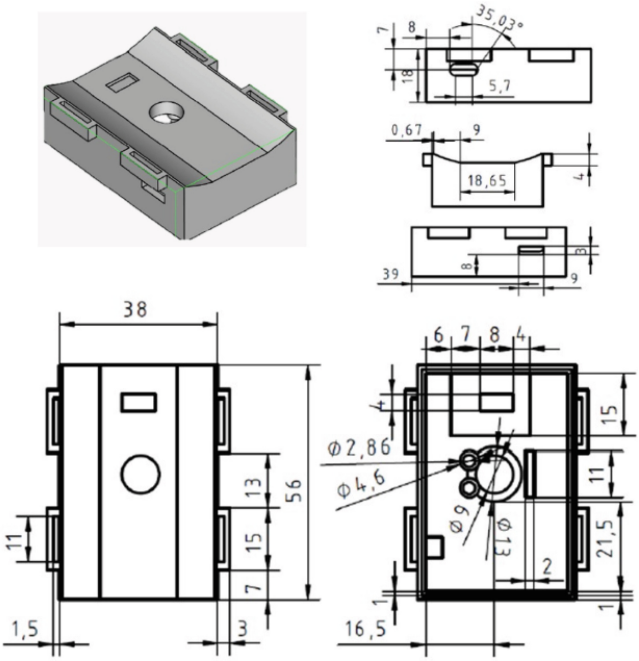

Fig. 3. 3D-printed PLA casing with its dimensions from various perspectives.

– n is the total number of values of the variable.

$$\hat{X} = \{X_i \mid f(X_i) = \max f(X)\} \tag{3}$$

where:

– $\hat{X}$ represents the mode of the variable.
– X_i represents the recorded values of the variable.
– $f(X_i)$ is the absolute value.
– $\max f(X)$ is the maximum observed value.

The fifth phase consists of presenting the data collected by the device on the TagoIO IoT platform. Communication between the device and TagoIO is established via the MQTT communication protocol. One of the most relevant features of TagoIO is its tool for defining threshold values, allowing the platform to send a notification if a received data point falls outside the established range. Figure 4 shows the TagoIO interface that monitors the study variables.

The final phase focuses on the development of a machine learning algorithm as in [17], which is based on training an LSTM model [18]. The model consists of 3 layers as in [19], divided into: a long short-term memory (LSTM) layer, a hidden dense layer with 100 neurons, and an output layer. The model runs a

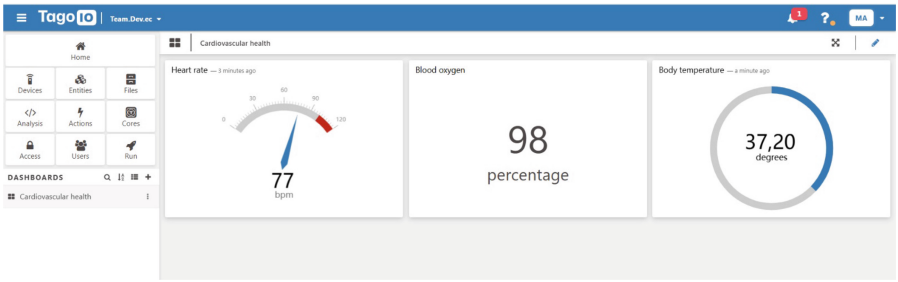

Fig. 4. Data monitoring from the TagoIO platform.

training loop for N epochs, during which it calculates the training and validation loss. The forward propagation is performed as follows:

$$\hat{y} = f(X; \theta) \tag{4}$$

– where: θ are the model parameters.

The loss function measures the difference between prediction and actual value:

$$L = \frac{1}{n} \sum_{i=1}^{n} \ell(\hat{y}_i, y_i) \tag{5}$$

Backpropagation is used and the weights are updated with:

$$\theta \leftarrow \theta - \eta \nabla L \tag{6}$$

The RMSE[4] is also calculated between the actual values and the predictions using the formula:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{7}$$

This model is developed using the Google Colaboratory tool and libraries such as TensorFlow and Torch [20,21]. In this way, the algorithm predicts unusual values in the data obtained from the device, playing an important role in the timely assistance of the patient to avoid potential cardiovascular health risks.

Although this study prioritizes LSTM due to its strength in temporal data modeling, future research will explore alternative models such as Gated Recurrent Units (GRUs), Random Forest Regression, and hybrid CNN-LSTM architectures to improve performance across all measured variables.

[4] Root Mean Square Error.

4 Results

4.1 Device Implementation

Figure 5 shows the installation of the device, which is placed on the index finger, as the sensors are located on the upper part. Adjustable Velcro straps are used to secure it, allowing it to be comfortably and safely fitted to any user. In this way, the device meets the goal of a non-invasive design for the patient.



Fig. 5. Device implementation.

4.2 Device Autonomy

Table 1 presents the individual power consumption of the ESP32C3 control unit and the sensors integrated into the electronic device. Additionally, the total consumption in milliamperes is shown.

Table 1. Shows the consumption of each component and the total consumption of the proposed device.

Component	Power Consumption
Xiao ESP32C3	75 [mA]
MLX90614	0.17 [mA]
MAX30100	1.2 [mA]
Total Consumption	76.37 [mA]

According to the characteristics of the lithium battery, which are 3.7 [V] and 500 mAh, the device's autonomy in hours is:

$$\text{Autonomy} = \frac{\text{Battery Capacity}}{\text{Device Consumption}} \tag{8}$$

$$\text{Autonomy} = \frac{500\,[\text{mAh}]}{76.37\,[\text{mA}]} \tag{9}$$

$$\text{Autonomy} = \frac{500\,[\text{mAh}]}{76.37\,[\text{mA}]} \tag{10}$$

$$\text{Autonomy} \approx 6.54\,[\text{h}] \tag{11}$$

Although the validation was conducted using the Xiaomi S1 Pro smartwatch, which complies with European Union standards—such as CE marking and the Radio Equipment Directive (RED)—ensuring consumer safety and wireless communication compliance, the study acknowledges the limitation of relying on a single commercial-grade device that is not medically certified. Future iterations will include comparisons against multiple certified medical-grade instruments to enhance the generalizability, statistical robustness, and clinical relevance of the findings.

4.3 Body Temperature Data Analysis

The scatter plot presented in Fig. 6 shows the temperature of a person without hypertension, comparing the readings of the proposed prototype (in blue) with those of the Xiaomi S1 Pro smartwatch (in red). The red dots (Xiaomi S1 Pro) are more evenly distributed around the 37.4 °C line, matching their statistical measures: a mean, median, and mode of 37.4 °C. On the other hand, the blue dots (proposed prototype) show greater variability, with temperatures fluctuating more widely, although its mean is 37.374 °C, the median is 37.37 °C, and the mode is 37.35 °C. Therefore, the proposed prototype may have slightly greater variability in its temperature readings compared to the Xiaomi S1 Pro smartwatch.

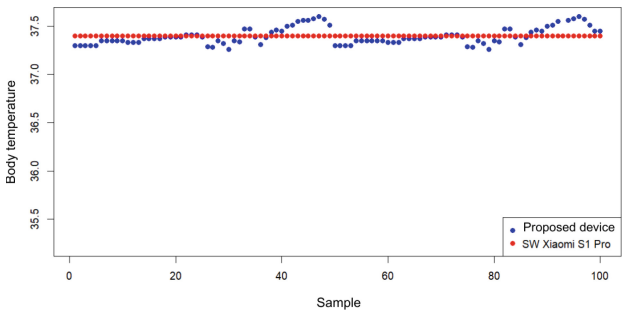

Fig. 6. Scatter plot of body temperature in a person without hypertension. (Color figure online)

The scatter plot presented in Fig. 7 shows the temperature of a person with hypertension, comparing the readings of the proposed prototype (in blue) with those of the Xiaomi S1 Pro smartwatch (in red). The red dots from the Xiaomi S1 Pro are grouped around 36.4 °C, which aligns with its mean and median of 36.496 °C and 36.4 °C respectively, showing a uniform and consistent distribution. In contrast, the blue dots from the proposed prototype show greater variability, with some significantly high values and more dispersed statistics: a mean of 37.1055 °C, a median of 36.29 °C, and multiple modes (6.81, 36.84, 36.87). This suggests that the prototype has greater dispersion in measurements, with several outliers, compared to the stability of the Xiaomi S1 Pro.

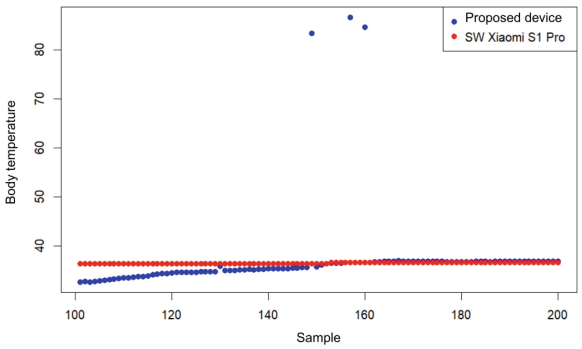

Fig. 7. Scatter plot of body temperature in a person with hypertension. (Color figure online)

Both compared devices have very similar means, medians, and modes (the prototype with a mean of 37.374 °C, a median of 37.37 °C, and a mode of 37.35 °C, and the smartwatch with 37.4 °C in all measures), but the prototype shows greater variability in its temperature readings. The red dots from the Xiaomi S1 Pro smartwatch are uniformly distributed around the 37.4 °C line, indicating more consistent stability compared to the blue dots from the prototype, which fluctuate more widely. This greater variability suggests that the prototype has slightly lower precision. Nevertheless, due to the proximity of the central measures, the reliability of the prototype can be estimated at 92%.

4.4 Machine Learning Model: LSTM Neural Networks

Figure 8 presents the prediction analysis of SPO2 using an LSTM model. SPO2 values range between 60% and 100%, and the predicted values by the model are compared with the actual values. The evaluation metrics indicate solid model performance: the Root Mean Square Error (RMSE) is 0.470, the Coefficient of Determination (R^2) is 0.733, meaning the model explains a significant portion of the data variability, and the Mean Absolute Error (MAE) is 0.241. These results

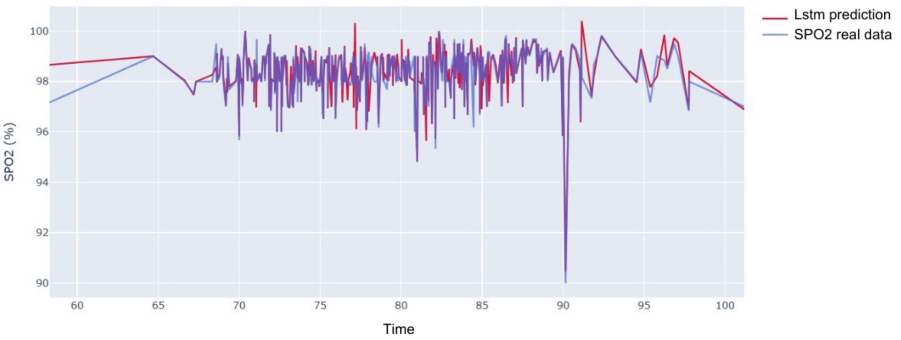

Fig. 8. Graph obtained from the LSTM model for SPO2.

show that the LSTM model has adequate predictive capability for estimating SPO2 levels.

Figure 9 presents an analysis of heart rate prediction using an LSTM model. The predicted values by the model are compared with the actual values, and evaluation metrics are presented to assess the model's performance. The Root Mean Square Error (RMSE) is 0.569, indicating a significant deviation between the predicted and actual values. The Coefficient of Determination (R^2) is 0.797, suggesting that the model explains only a small portion of the variability in the data. Additionally, the Mean Absolute Error (MAE) is 0.346, reinforcing the idea that the model has limited performance in predicting heart rate.

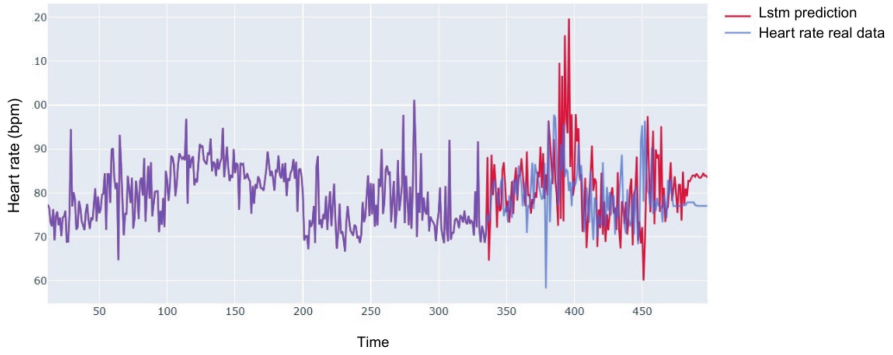

Fig. 9. Graph obtained from the LSTM model for heart rate.

Figure 10 describes the analysis of temperature prediction using an LSTM model. The predicted values by the model are compared with the actual values, and evaluation metrics are presented to assess the model's performance. The Root Mean Square Error (RMSE) is 1.534, indicating a relatively low deviation between the predicted and actual values. The Coefficient of Determination (R^2)

is 0.847, suggesting that the model explains a large portion of the data variability. Furthermore, the Mean Absolute Error (MAE) is 0.527, reinforcing the idea that the model has solid performance in temperature prediction.

4.5 Discussion

In the studies by [6–9], although methods are proposed to improve the accuracy of the data obtained from the MAX30100 sensor, the temperature variable is not considered. According to the present study, this variable is important in monitoring patients with hypertension problems, as it is directly related to blood pressure. Based on these findings, the importance of including temperature in the analysis is highlighted to ensure a more comprehensive follow-up of the patient's condition.

Regarding the prototypes analyzed in the reviewed works, there is a lack of design for devices that are ergonomic and non-invasive for the patient. To overcome these limitations, an innovative prototype has been developed that is placed solely on the finger, allowing measurement of heart rate, blood oxygenation, and body temperature. This compact and portable device includes a battery that ensures its autonomous operation, offering an efficient solution for continuous patient monitoring. Unlike existing commercial devices that are often costly and require professional calibration or frequent replacement parts, the proposed prototype offers affordability (<$50), full open-source compatibility, and simplified maintenance. Its ergonomic design, using 3D-printed PLA and minimal electronic components, ensures both portability and comfort—attributes not always prioritized in current market options.

In addition, there is a growing trend toward connecting electronic devices to the cloud. In this context, related applications include real-time monitoring screens, remote data visualization, and the use of databases and local servers. Conventional IoT protocols, such as HTTPS requests[5], are used for this purpose. However, these protocols are inefficient for battery-operated devices, as they consume a significant amount of energy. Therefore, it is advisable to use

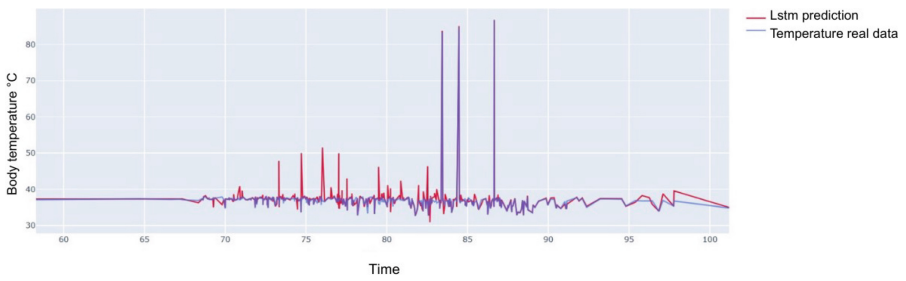

Fig. 10. Graph obtained from the LSTM model for body temperature.

[5] Hypertext Transfer Protocol Secure.

lighter and more specific protocols, such as MQTT[6]. In this sense, the present proposal opts for the use of the MQTT protocol, which offers significant advantages by allowing the management of multiple simultaneous connections without compromising device performance, ensuring continuous operation.

Despite promising results, the prototype has not yet undergone formal clinical validation. Future deployments will include trials in collaboration with certified medical institutions to assess diagnostic reliability in real-world scenarios and under diverse patient conditions.

Finally, regarding the predictions of the study variables, it is important to highlight the need to design health devices that not only focus on controlling and monitoring data through IoT but also integrate learning models using current technology. These models serve as essential tools for preventing cardiovascular health issues, allowing healthcare professionals to intervene in a timely manner before complications arise.

5 Conclusions

This work presents the design and development of a non-invasive device for people with a history of cardiovascular diseases. The proposed device aims to collect and monitor signals of heart rate, blood oxygen levels, and body temperature. The signals are collected using sensor modules integrated with a microcontroller, and the data are transmitted using IoT protocols such as MQTT to the TagoIO platform.

According to the data analysis and comparison with the smartwatch, the following results were obtained: the proposed device showed results similar to those of a smartwatch, with measurements of 77.49 bpm for heart rate, 98.79% for SpO2, and 37.37 °C for body temperature. In comparison, the smartwatch recorded 75.38 bpm, 98%, and 37.4 °C, respectively.

The work also focused on the implementation of a prediction model based on artificial neural networks. We introduced a three-layer process with 100 neurons. The algorithm was applied to the three study variables, calculating the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), and the Coefficient of Determination (R). These values are essential for evaluating the learning performance and improving prediction accuracy. This prediction method is crucial for triggering early alerts in case of unusual signal values from the patient, enabling timely medical assistance.

Compared to conventional wrist-worn smartwatches, the proposed device achieves a similar level of signal reliability while significantly reducing manufacturing costs. The simplified design also eliminates dependency on proprietary platforms, making it a scalable solution for low-resource healthcare environments.

As future research, the integration of additional modules such as an electrocardiograph (ECG) is proposed to enhance the robustness of the system and

[6] Message Queuing Telemetry Transport.

enable more comprehensive cardiovascular monitoring, while preserving the non-invasive and portable nature of the device. Furthermore, to improve the predictive accuracy across all vital signs, future work will explore alternative machine learning models beyond LSTM, including Gated Recurrent Units (GRUs), Random Forest Regression, and hybrid CNN-LSTM architectures, aiming to optimize performance and adaptability in diverse health monitoring scenarios.

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