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# A Low-Cost IoT Wearable Device with XGBoost, CNN and SVM for Early Detection of Fever, Tachycardia and Hypoxia

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**Abstract.** Chronic and cardiovascular diseases present a significant global health threat, underscoring the need for remote monitoring technologies capable of ensuring continuous and accessible care. Vital signs such as body temperature, heart rate, and blood oxygen saturation are critical indicators for early detection of health alterations. This study proposes the design of a low-cost wearable device with non-invasive sensors for real-time acquisition and processing of these variables, integrating machine learning algorithms including Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and XGBoost. A dataset of 2,480 samples (2,130 experimental, 350 public) was used for training and validation. The models achieved high predictive performance, with XGBoost obtaining an $R^2$ of 0.9765, accuracy of 95.8%, and F1-score of 0.96, surpassing SVM and CNN. These results highlight the potential of combining affordable wearable devices with advanced ML to enable early detection, preventive monitoring, and scalable healthcare solutions.

**Keywords:** Wearable Device, Machine Learning, XGBoost, CNN, SVM, Healthcare, remote monitoring, body temperature, heart rate, oxygen saturation.

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## 1 Introduction

Cardiovascular diseases (CVDs) remain one of the leading causes of morbidity and mortality worldwide, driven by multifactorial etiologies that involve biomarkers, diagnostic imaging techniques, pharmacological interventions, and lifestyle-related factors [1]. This approach advocates for the implementation of preventive strategies, encompassing regular physical activity and the pharmacological treatment of patients with chronic diseases. These strategies have been demonstrated to yield substantial benefits in terms of mitigating cardiovascular complications [2]. Additionally, the burden of these diseases on vulnerable groups is noteworthy, particularly in family caregivers, a population shown to present elevated cardiovascular risk due to sustained levels of stress [3].

The challenges posed by the SARS-CoV-2 (COVID-19) pandemic exposed significant vulnerabilities in healthcare systems, most notably hospital overcrowding and limited access to timely medical care. In this context, digital health solutions with a focus on cardiovascular care have emerged as a response to the demands for continuous monitoring and treatment [4]. In response, research has focused on methods and solutions for diagnosing diseases and providing effective treatments through monitoring systems that can be implemented outside the hospital environment [5, 6].

Concurrently, alternatives in remote health monitoring have emerged, presented by recent advances in portable technologies and smart mobile devices based on data collection [7]. These non-invasive portable devices are equipped with biosensors that allow continuous measurement of physiological parameters such as oxygen saturation, heart rate, and body temperature. Consequently, these systems are presented as a tool that facilitates disease detection. Additionally, they incorporate communication technologies such as the Internet of Things (IoT), facilitating real-time connectivity and the collection of biometric data [8].

Recent advancements in IoT have significantly contributed to the development of healthcare and health monitoring systems. This technology enables real-time storage of biometric data, addressing critical challenges such as latency, scalability, and network reliability [9]. Moreover, they have transformed clinical practice by providing healthcare professionals with continuous, remote access to patients' physiological data, facilitating communication and care, and improving treatment outcomes [10, 11]. These capabilities are largely supported by the growing integration of WD equipped with advanced biosensors.

This digital transformation has had a significant impact on the adoption of Wearable Devices (WD) in various sectors, including healthcare, sports, and industry. The utilization of biomedical sensors, integrated into medical devices, has seen a marked increase in applications involving continuous monitoring of vital signs. This practice is particularly relevant in the context of the treatment of chronic and cardiovascular diseases. Recent advancements in sensor technologies, including fiber optic-based biosensors, have enhanced the accuracy and efficiency of data collection, thereby rendering them a viable option for personalized medicine practices [12–14].

Furthermore, biosensors have emerged as pivotal instruments in health assessment, encompassing both normal physiological conditions and pathological states. This phenomenon can be attributed to the fact that body temperature serves as a vital indicator in the diagnosis of infections and inflammatory processes. In contrast, heart rate and its variability have been identified as significant predictors of cardiovascular health, offering insights into factors such as stress and cardiac abnormalities [15, 16]. The quantification of these parameters is facilitated by the IoT-enabled WD, thereby enabling the early detection of diseases and promoting early intervention. This underscores their significance in contemporary health monitoring systems [17] and proposes the implementation of intelligent algorithms capable of interpreting data such as vital signs.

Machine learning (ML) and deep learning (DL) algorithms have emerged as a fundamental component of health monitoring technologies. These methods facilitate the analysis of voluminous and intricate data sets, enhancing the discernment of latent patterns and underpinning precise diagnostic and predictive models [18]. The integration of ML into IoT-based healthcare systems facilitates the development of monitoring frameworks that enhance measurement accuracy and enable the real-time detection of critical events [19]. This transition to individualized medicine has enabled the development of systems that can predict disease progression and enhance treatment delivery [20]. Temperature monitoring is an example of this phenomenon. This field has seen significant advancements due to the integration of ML models. These models have been developed to correlate peripheral measurements with estimates of core temperature. The result of this integration is more reliable health assessments [21].

This work contributes to the field of digital health by presenting low-cost WD equipped with non-invasive sensors for the acquisition of vital signs such as body temperature, heart rate, and blood oxygenation. In contrast to numerous existing devices that necessitate direct skin contact or depend on costly technologies, this WD emphasizes affordability and accessibility, rendering it suitable for environments with limited resources. Furthermore, the incorporation of ML and deep learning algorithms (SVM, CNN, and XGBoost) has been demonstrated to enhance predictive capacity, thereby enabling the early identification of conditions such as fever, tachycardia, and hypoxia. The integration of real-time IoT connectivity, cost-effective design, and advanced analytics signifies the primary novelty of this study, thereby positioning it as a scalable and practical solution for continuous health monitoring and preventive medicine.

This paper is organized as follows: Section 2 presents a comprehensive review of related works. Section 3 provides a detailed description of the architecture employed for WD design, the establishment of connections to components, and the methodology of data acquisition. Section 4 presents the application of ML models, classification models, evaluation metrics, and data split. The experimental results and their respective analyses are presented in Section 5, while the discussion is presented in Section 6. Finally, Section 7 presents the conclusions and limitations observed.

## 2 Related Works

The research presented in [22, 23] reviews the development of wearable devices that quantify microcirculatory parameters for cardiovascular monitoring. The review highlights advance in clinical validation and demonstrate the potential for continuous, non-invasive measurement of data such as blood pressure. In addition, the study by [24] reviews wearable biosensors designed for cardiovascular health monitoring. It covers technologies such as photoplethysmography (PPG), electrocardiography (ECG), and nanomaterial-based sensors. The studies also emphasize the use of artificial intelligence for predictive analysis and the early detection of cardiovascular abnormalities.

A study conducted in [25, 26] presents a clinical evaluation of a wrist device designed to monitor hospital patients. It measures heart rate, blood pressure, and oxygen saturation, which enable early intervention through alerts. The authors in [27, 28] describe the development of a portable device that can monitor vital signs, such as blood oxygen saturation, heart rate, and body temperature. This system is designed with low-cost, integrated sensors that demonstrate the reliability of this type of device for medical use. In contrast, the document in [29] analyzes the reliability of using smart devices, such as smartphones, to quantify vital signs, such as peripheral oxygen saturation and heart rate, in hypotensive patients.

The paper by [30, 31] discusses the use of a hybrid temperature compensation system for piezoresistive strain sensors. The system improves the accuracy of the sensors under variable environmental conditions, ensuring the reliability of wearable devices for physiological monitoring. Authors [32, 33] developed a high-performance, multifunctional sensor based on a rubber and carbon nanotube (CNT) matrix that can detect human movement and skin temperature. This flexible device's design makes it a promising platform for applications in DV. Conversely, [34] addresses stress detection using data acquired by portable physiological sensors that integrate signals such as heart rate, heart rate variability, and skin conductance to identify stress states in real time.

In [35], a review of the integration of DV with IoT is presented, highlighting applications for healthcare and sports. Opportunities for personalized care are identified, as well as challenges related to data security and system operation. In addition, in [36], the authors explore the development of microwave devices applied to wearable sensors and IoT communications, demonstrating the application of technologies such as radio frequency to improve the energy efficiency of monitoring systems. Concurrently, in [37], a thorough review of IoT applications for wearable technologies is conducted, examining use cases in health monitoring and remote patient management.

The review of related work in [38] discusses the use of deep learning and machine learning tools for applications related to healthcare systems. These address existing taxonomies, the challenges of interpreting information, cybersecurity, and the need to ensure privacy and robustness in models for clinical application. Therefore, [39, 40] address the challenges of implementing these techniques in real medical settings, emphasizing the importance of prioritizing data quality and management over model building. They also discuss the potential of deep networks for health time series prediction, with applications in early detection and diagnosis of diseases.

## 3 Implementation of Wearable Device Architecture

The Digital National Observatory of Intelligent Environments (OBNiSE) has presented architecture for the development of IoT-based WD in [41, 42]. OBNiSE is part of the Center for Research, Innovation, and Technological Development of the Universidad del Valle de México (CIIDETEC-UVM). In consideration of the aforementioned factors, architectural design has been conceived as an integrated system. Design purpose is to enable the control, analysis, supervision, and development of intelligent systems, as illustrated in Figure 1. The objective is to create IoT-based solutions, while ensuring the security and efficient management of large volumes of data at different levels.

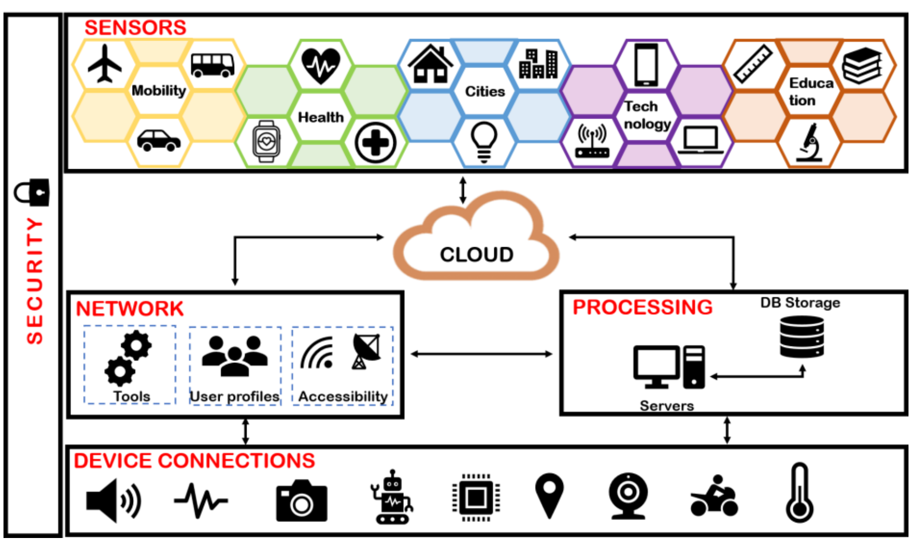


**Fig. 1.** OBNiSE architecture-based intelligent healthcare system.

The implementation of the modules necessary for the operation, data analysis, and communication of the WD is proposed, based on the architecture presented. The modules implementation is illustrated in Figure 2. The subsequent sections delineate the components of each module.

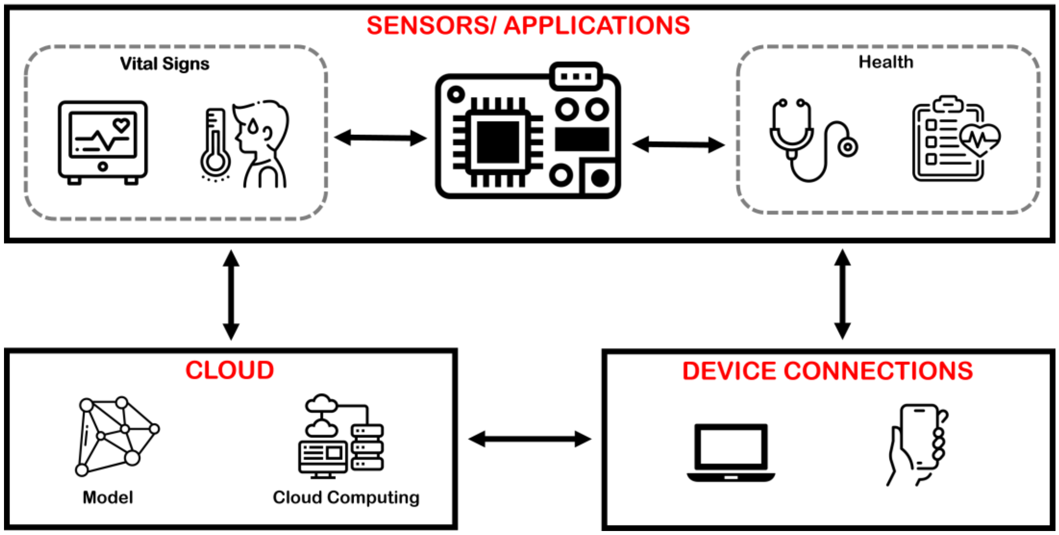


**Fig. 2.** Design and implementation of IoT solutions with OBNiSE architecture.

The proposed architecture is structured into three main modules:

- Sensors/Applications: This module integrates the physiological sensors with the microcontroller, enabling the acquisition of vital signs and the development of a functional wearable device for health monitoring.
- Cloud: This component manages device connectivity and is responsible for the secure storage, processing, and management of the data collected by the sensors.
- Device Connections: This module encompasses smart devices (such as mobile phones or computers) that interface with the wearable system, allowing users or healthcare professionals to access, visualize, and analyze the transmitted data.

## 3.1 Remote devices and Networks

The WD is composed of a microcontroller, a non-invasive sensor, and a blood oxygenation sensor and heart rate monitor implemented at the wrist. The configuration of the system is illustrated in Figure 3, and a detailed description is provided below.

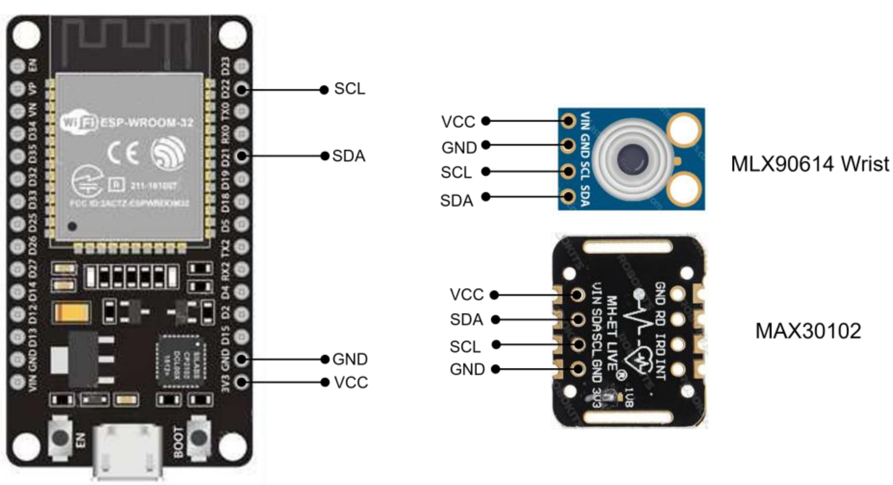


**Fig. 3.** WD connections.

This system is designed for the measurement and collection of biometric data using sensors such as the MLX90614, which is an infrared sensor known for its accuracy and stability in biomedical applications, used to measure temperature, and the MAX30102 sensor, as demonstrated in Figure 4, which integrates the necessary elements for detecting heart rate and blood oxygen levels on a single chip. The system incorporates light emitters, photodetectors, and electronic circuits that are optimized to reduce noise and minimize the influence of ambient light. The architecture of the device necessitates two distinct power supplies (Volts, V), specifically 1.8V for the module and 3.3V for the light-emitting diodes (LEDs). It employs a standard I2C bus to facilitate communication. The device is equipped with a software-controlled shutdown mode that eliminates standby power consumption while maintaining active power lines.

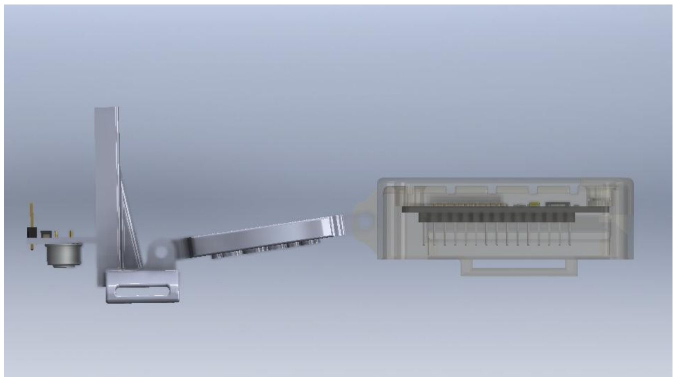

**Fig. 4.** WD 3D design.

## 3.2 Data acquisition

During the data collection process, a work plan was implemented in which sensors were installed at wrist height on thirty participants to measure temperature, heart rate, and blood oxygenation, as illustrated in Figure 5 and specified in Table 1. Moreover, the participants in this study were recruited from the Autonomous University of Zacatecas and ranged in age from 19 to 24 years. It is noteworthy that their health status was not taken into consideration during the measurement stage. A more detailed description of the experiment and data acquisition can be found in [43].

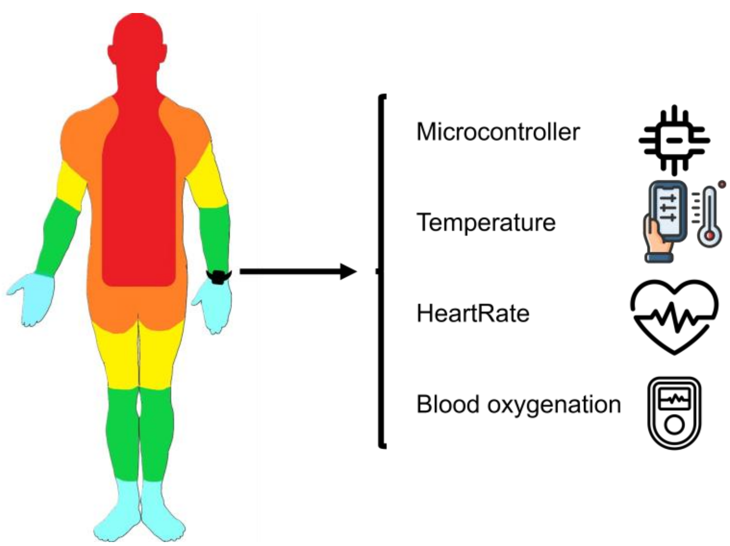


**Fig. 5.** WD implementation.

**Table 1.** Variables measured by WD

| Nomenclature | Variable type | Measurement unit |
|---|---|---|
| T | Temperature | °C |
| HR | Heart Rate | BPM |
| SpO2 | Oxygen saturation | % |

Prior to the measurement of the variables, the participants underwent an acclimatization period of approximately ten minutes. This period allowed the participants to stabilize their physiology and adapt to the ambient temperature. After completing the acclimatization process, the WD was installed, and the participants engaged in physical activity for a period of fifteen minutes. During this period, the system collected data at periodic intervals of 14 to 16 seconds, an interval determined by the latency characteristics of the IoT infrastructure. This resulted in a total of 2,130 records being collected.
The monitoring procedure entailed the consideration of three key physiological variables: body temperature, heart rate, and blood oxygenation. For this purpose, the WD was positioned on the participant's wrist, allowing for non-invasive recording of vital parameters. Subsequently, the data was automatically transmitted to a cloud platform, thereby facilitating secure storage in addition to enabling advanced processing and real-time data analysis.

## 4 Machine learning and evaluation models

In the domain of health monitoring, multiple ML algorithms have been deployed to enhance the identification and forecasting of anomalies associated with vital signs. The relevant approaches include convolutional neural networks (CNN), support vector machines (SVM), and eXtreme Gradient Boosting (XGBoost).

CNN has demonstrated efficacy in the processing of multidimensional physiological data. This is due to their capacity to automatically extract hierarchical features and identify complex spatiotemporal patterns. These characteristics render the algorithm well-suited for the analysis of variations in parameters associated with temperature, heart rate, and oxygen saturation, where fluctuations may serve as indicators of these data's conditions. SVM are renowned for their efficacy in classification tasks, particularly in scenarios characterized by high-dimensional data or limited training sample sizes. The construction of optimal hyperplanes by SVMs enables the reliable separation of normal and pathological states, thereby ensuring robust performance in the presence of noise or imbalanced datasets. XGBoost, a gradient boosting framework, offers high accuracy, computational efficiency, and advanced mechanisms for handling missing values. The model's extensive set of hyperparameters enables fine-tuning to adapt to different types of data distributions and prediction tasks, rendering it an effective tool for detecting health anomalies such as fever, hypertension, and hypoxia.

These algorithms enable the comprehensive customization of the model training process. This flexibility facilitates fine-tuning of the model to optimize performance and adapt to the specific characteristics of the dataset and the nature of the task at hand.

### 4.1 eXtreme Gradient Boosting

XGBoost has gained recognition for its exceptional efficiency and predictive capabilities, rendering it particularly valuable in competitive data science challenges and analytical applications. A significant benefit of this algorithm is its robust approach to handling missing values. Rather than discarding incomplete records, it employs internal estimation strategies to ensure the integrity of the dataset. Furthermore, its scalability and adaptability enable effective management of large-scale datasets while addressing a range of tasks, including classification, regression, and prediction problems [43].

The general objective function of XGBoost is defined as follows:

$$L(\theta) = \sum_{i=1}^{n} l(\hat{y}_i, y_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{1}$$

where:

- I the loss function.

- $yi$ is the real value of sample i.
- $\hat{y}\imath$ is the prediction for iteration t.
- $\Omega(fk)$ is the regularization term of tree k.

## 4.2 Support Vector Machine

SVM are supervised learning models widely used for classification and regression tasks. Their main objective is to find the optimal hyperplane that maximizes the margin between data points of different classes. This approach provides high generalization ability, making SVM robust when working with high-dimensional datasets or when the number of training samples is limited. One of the key strengths of SVM is its ability to handle both linear and non-linear problems using kernel functions, enabling the transformation of data into higher-dimensional spaces where separation is more feasible.

The general objective function of SVM is defined as follows:

$$\underset{w,b,\xi}{\text{Min}} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i \tag{2}$$

Subject to:

$$y_i(w \cdot x_i + b) \geq 1 - \ \xi_i,\ \xi_i\ \geq 0 \tag{3}$$

Where:

- $w$ is the weight vector that defines the hyperplane.
- $b$ is the bias term.
- $\xi_i$ are slack variables allowing misclassification.
- C is the regularization parameter controlling the trade-off between margin maximization and classification error.

## 4.3 Convolutional Neural Network

CNN are a class of deep learning models designed to process multidimensional data and extract hierarchical features automatically. CNNs are particularly effective for detecting complex spatial and temporal patterns, making them highly useful in domains such as image recognition and physiological signal analysis. Their structure is composed of convolutional layers, pooling layers, and fully connected layers, which together enable the identification of relevant features without the need for manual feature engineering.

The operation of a convolutional layer can be expressed as:

$$h_{i,j}^{(k)} = f\ (\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} w_{m,n}^{(k)}\ \cdot\ x_i + m, j + n + b^{(k)} \tag{4}$$

where:

- $h_{i,j}^{(k)}$ is the activation at position (i,j) in the k-th feature map.
- $w_{m,n}^{(k)}$ are the learnable weights, convolutional kernel.
- $x_i + m, j + n$ represents the input values within the receptive field.
- $b^{(k)}$ is the bias for the k-th filter.
- $f(\cdot)$ is the activation function, commonly ReLU.

## 4.4 Evaluation models

The coefficient of determination (R-squared, $R^2$), a statistical measure of how well the independent variables explain the variation in the dependent variable, was employed to assess all associations. This metric is indicative of the model's goodness of fit and is defined by the following equation.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}\left(y_i - \underline{y}\right)^2} \tag{5}$$

A multitude of approaches underscore the potential for relationships between dependent and independent variables when applying algorithms to predict continuous outcomes. The selection of an appropriate evaluation metric is imperative, as it provides valuable insight into the relationship between the studied phenomenon and the research objective. In this study, a range of metrics were employed to evaluate the performance of the model, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Collectively, these measures furnish a comprehensive perspective on the model's accuracy and efficiency, thereby enabling a more precise interpretation of how the analyzed data reflects the underlying phenomenon [43].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_1})^2} \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_1| \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_1|}{y_i} \tag{8}$$

Where $n$ is the number of observations and $yi - xi$ is the error between the predicted and actual values.

The RMSE is a standardized form of the MSE, which evaluates the variance and measures the model's fit to the training data. RMSE amplifies the effect of larger errors by assigning them greater weight, meaning that a single inaccurate prediction can significantly influence the overall error, as expressed in the corresponding equation. Alternatively, MAE is a quantitative metric that calculates the mean absolute deviation between predicted and observed values. In contrast to the RMSE, the MAE does not impose an unduly severe penalty on outliers, thus providing a smooth and bounded metric of model performance. Finally, the MAPE is a statistical metric that evaluates the accuracy of a model's predictions in relative terms, expressing errors as percentages of the observed values. This metric is particularly useful when variations are more relevant than absolute magnitudes, as represented in its mathematical formulation.

## 4.5 Classification models

The following equations are defined to enable quantitative evaluation of model performance when making case predictions, as indicated by the classification metrics: This accuracy is a measurement of the overall proportion of cases that have been correctly classified, and it generates indicators of the algorithm's predictive power. Accuracy is a metric that quantifies the proportion of positive cases that are correctly predicted among all positive cases. It is a measure of the reliability of the model in minimizing false positives. Similarly, recall quantifies the proportion of actual positive cases that were correctly identified, thereby promoting relevance in applications where it is critical to avoid missing true positives. The F1-score integrates precision and recall into a harmonic measure, thereby providing a balanced and robust metric for cases characterized by uneven class distribution [44].
A comprehensive framework for the analysis of classification models is subsequently formulated, ensuring a more profound understanding of the strengths and limitations of each of the ML algorithms employed for specific task management.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{12}$$

Where:

- TP (True Positive) is equivalent to instances classified as positive that belong to the positive class.
- TN (True Negative) is indicative of cases classified as negative, which, in essence, belong to the negative class.
- FP (False Positive) are cases classified as positive when they belong to the negative class (type I error).
- FN (False Negative) cases are classified as negative when they are positive cases (type II error).

### 4.5 Data split

The dataset utilized for the implementation of ML algorithms was partitioned into 70% for training and 30% for testing, a common strategy that allows optimizing model performance and improving the reliability of evaluations. This division was applied to both the database collected from experimental measurements of vital signs and to a complementary public database oriented to the health domain [45]. The computational environment was developed in Google Colab, leveraging the Python programming language. The management and preliminary processing of the data was executed through the utilization of Pandas for the purpose of tabular analysis and NumPy for the execution of mathematical operations.

In the ML stage, various algorithms were implemented in accordance with their distinct strengths. The implementation of XGBoost was motivated by its demonstrated efficacy in classification and regression tasks, particularly its efficient handling of missing values and its high predictive performance. SVM were employed to construct optimal hyperplanes that maximize the separation between classes, thereby ensuring high accuracy in binary and multiclass classification problems. Likewise, Convolutional Neural Networks CNN were utilized to automatically extract spatial and temporal features from physiological signals, thereby enabling the identification of complex patterns without the necessity of manual feature engineering.

Finally, the evaluation and visualization processes were supported with libraries such as sklearn (for preprocessing, training, and validation of models) and Matplotlib (for graphical representation and result analysis).

## 5 Results

The results section presents the findings derived from using the ML algorithms and the comprehensive data analysis described above. These results provide a comprehensive view of the interdependencies evaluated using mathematical correlation equations and the application of predictive models. In addition, the accuracy of the data obtained was validated and compared.

The application of ML algorithms was contingent upon the presence of three primary conditions, as determined from the available vital signs, including fever, tachycardia, and symptoms of hypoxia. As illustrated in Figure 6, the data trend and the distribution of physiological variables are presented in tandem, underscoring the significance of each vital sign in the predictions and the distribution of their values. Box plots are employed to illustrate medians, quartiles, and potential outliers, thereby facilitating the discernment of patterns, anomalies, and variability in body temperature, heart rate, and oxygen saturation across the diverse groups examined. This representation facilitates understanding of the relative impact of each variable on the conditions evaluated and offers a comprehensive view of the behavior of the data.

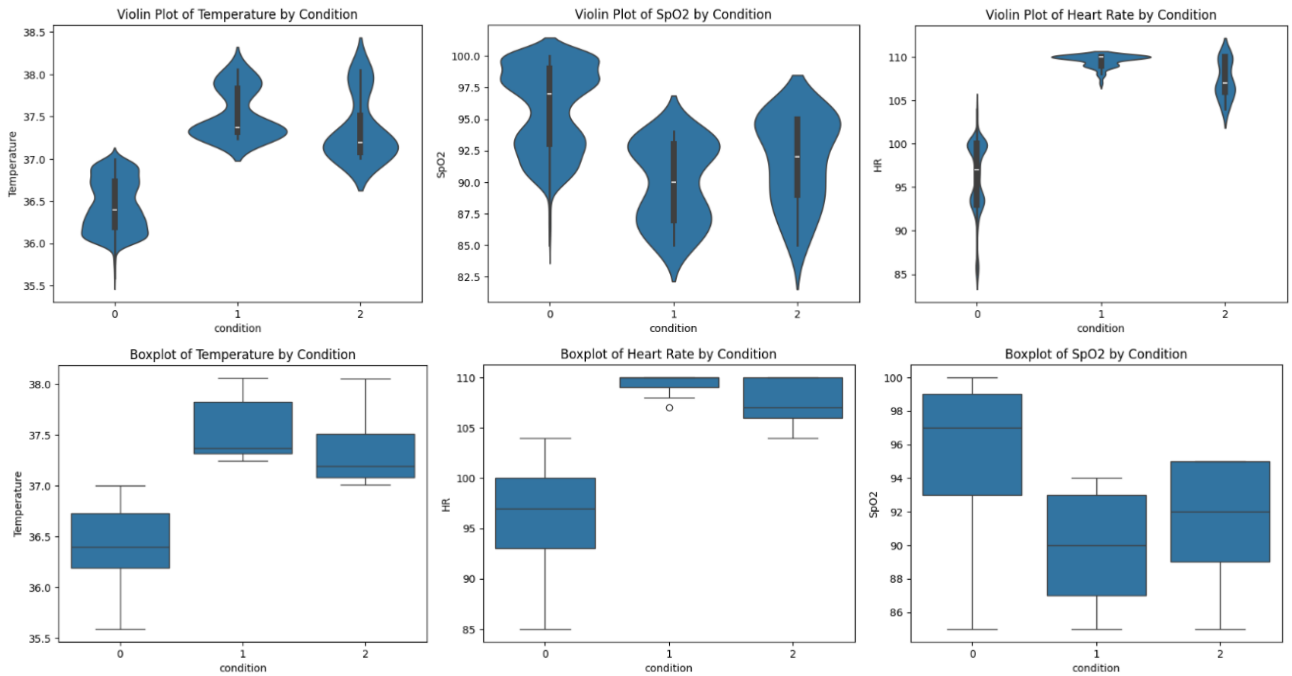


**Fig. 6.** Data trend and boxplot for each condition.

Furthermore, a correlation matrix was developed to assess the relationship between the variables in the data set. This matrix is essential because it identifies the strength and direction of linear relationships between variables, as demonstrated in Figure 7. This analysis is critical for comprehending the interdependence between vital signs and can unveil significant patterns that influence model predictions. The information obtained from the correlation matrix has been demonstrated to facilitate the improvement of feature selection and the optimization of the predictive model's performance.

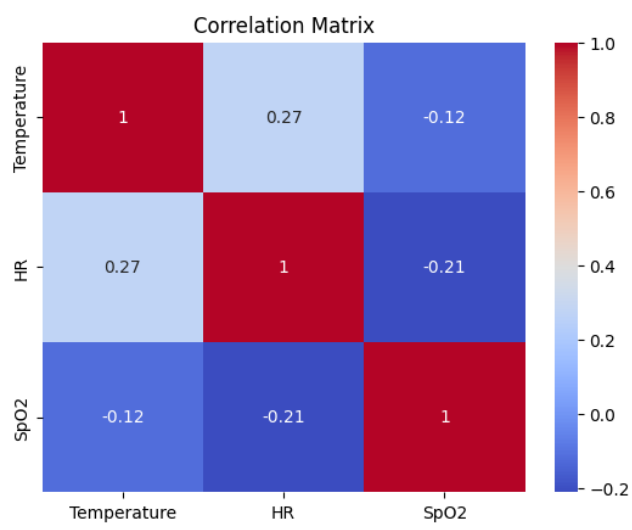


**Fig. 7.** Variables correlation matrix.

## 5.1 ML algorithm results

A confusion matrix is implemented to evaluate the performance of the classification models, as it provides a detailed visualization of how predicted labels compare to the actual values. This tool is designed to reflect the overall accuracy of the models and to highlight specific misclassifications. As a result, it is possible to identify the strengths and weaknesses in the detection of each condition. In this study, confusion matrices were generated for the three algorithms implemented XGBoost, CNN, and SVM to analyze their ability to correctly classify the conditions of fever, tachycardia, and hypoxia, as well as the absence of these, this is shown in Figure 8. A quantitative comparison of the matrices reveals the extent to which each algorithm manages class separability, the degree of precision in correctly identifying conditions, and the type of errors committed. This comparative visualization facilitates a more accurate interpretation of the model's behavior, offering valuable insights into potential areas for enhancement to improve its predictive performance.

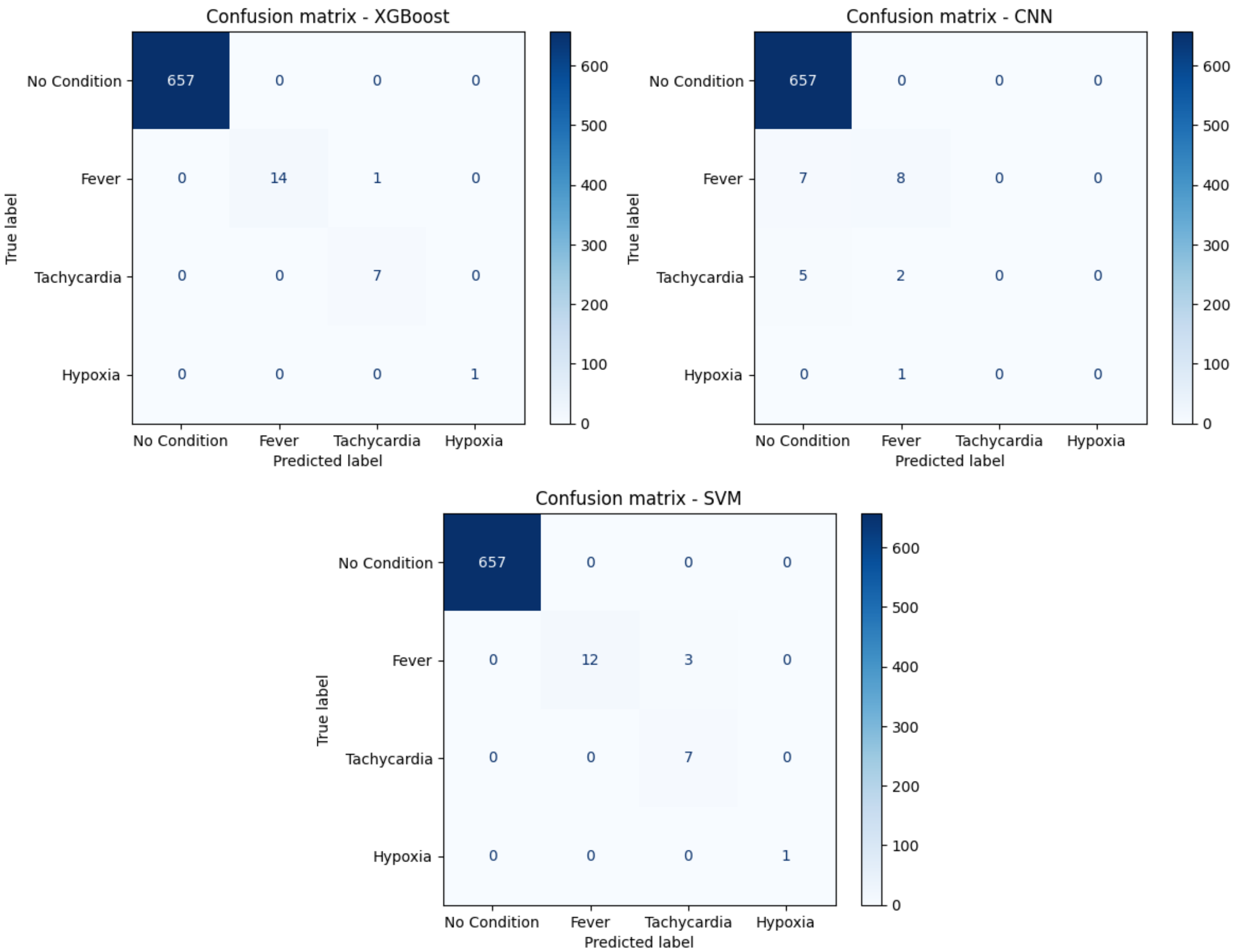


**Fig. 8.** Confusion matrices of XGBoost, CNN, and SVM models for condition classification.

The models were evaluated using the metrics MAPE, MAE, RMSE, and R2. These metrics provided a comprehensive view of the ML models' performance in predicting fever, tachycardia, and hypoxia from vital signs. The results of this validation process are presented in Table 2, including the predictive performance and error analysis for each model. In contrast, the efficacy of the algorithms was assessed employing classification metrics such as accuracy, precision, recall, and F1-score. These metrics provide a comprehensive framework for quantifying the effectiveness of models in differentiating between different health conditions. The results obtained have been summarized in Table 3, which provides an overview of the classification capability.
Additionally, the evaluation of feature relevance across the models revealed that body temperature is the strongest predictor for fever, heart rate contributes most significantly to tachycardia classification, and $SpO_2$ is the dominant variable for detecting hypoxia. These results align with the physiological significance of each parameter and support the suitability of the selected models for vital-sign classification tasks.

**Table 2.** Results obtained from evaluation models

| Model | RMSE | MAE | MAPE | $R^2$ |
|---|---|---|---|---|
| XGBoost | 0.0383 | 0.0014 | 4.3478 | 0.9801 |
| CNN | 0.1434 | 0.0176 | 15.942 | 0.7058 |
| SVM | 0.0664 | 0.0044 | 13.043 | 0.9405 |

**Table 3.** Results obtained from classification models

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| XGBoost | 0.9985 | 0.9987 | 0.9985 | 0.9985 |
| CNN | 0.9838 | 0.9801 | 0.9838 | 0.9807 |
| SVM | 0.9955 | 0.9969 | 0.9955 | 0.9957 |

## 6 Discussion

The integration of wearable devices with IoT and ML has profoundly impacted the field of healthcare. This integration has enabled continuous and real-time monitoring of vital signs, including heart rate, body temperature, and blood oxygen saturation [22–41]. The integration of IoT in these systems facilitates seamless communication, remote data acquisition, and cloud-based processing, thereby enhancing the capacity for medical follow-up and supporting timely interventions, particularly in the management of chronic diseases [26, 27]. In contrast, the present work focuses on the development of a low-cost wearable device specifically designed to estimate body temperature through wrist measurements. While numerous IoT-enabled devices reported in the extant literature emphasize complex multi-parameter monitoring systems, the approach presented here prioritizes affordability and targeted application without compromising accuracy. This strategy is a response to the growing need for accessible healthcare technologies that can be widely implemented in diverse contexts [30–32].

The incorporation of ML methodologies has the potential to enhance the capabilities of wearable devices by enhancing the precision of predictive analytics. By analyzing temperature data from the wrist, ML algorithms can provide precise estimates of body temperature, facilitating the early detection of fever and other temperature-related conditions. This predictive component aligns with contemporary research trends, wherein ML enhances the diagnostic and preventive capabilities of wearable technologies. Additionally, this approach is distinguished by its emphasis on cost-effectiveness and specialized use cases [35–36]. Moreover, extant literature on IoT and ML predominantly emphasizes real-time data collection and retrospective monitoring. In contrast, the present study introduces a proactive element by addressing the prediction of potential health issues before their manifestation. This predictive capacity is of growing importance in modern healthcare systems, where early intervention can lead to significant improvements in patient outcomes [37–41].

A study limitation is the relatively small size of the samples obtained, which may affect the performance and generalization of the classification and evaluation models. A limited dataset may restrict the model's ability to capture the variability of physiological signals and may increase the risk of overfitting, which could mean lower classification accuracy for larger populations. Cross-validation techniques were applied during the training process to verify the stability of the model and minimize bias, thus helping to mitigate the problem. Despite the preliminary nature of this experiment and the limited amount of data, the results provide valuable information on the relative performance of different algorithms for physiological signal classification. These findings underscore the proposed approach's potential and lay the foundation for future studies with larger and more diverse datasets. These studies will enhance the robustness of the model and its clinical applicability.

A considerable volume of research has utilized ML methodologies, including SVM, Random Forests, and CNN, to forecast diseases based on vital signs. While these methods have yielded encouraging results, they are confronted with significant challenges, including the management of incomplete datasets, the risk of overfitting, and constrained adaptability to varied conditions. In this context, XGBoost has emerged as a robust alternative, thanks to its regularization mechanisms, efficient optimization strategies, and flexibility in adapting to different data structures. These advantages have positioned it as one of the most competitive algorithms in predictive healthcare tasks. Therefore, the discourse on ML in the context of wearable health monitoring underscores the strengths and limitations of diverse methodologies. While methods such as SVM and CNN have contributed valuable perspectives, XGBoost has demonstrated superior adaptability and resilience in managing real-world healthcare data. This finding serves to reinforce the potential of combining wearable technologies with advanced ML techniques to develop more precise and accessible predictive health tools.

## Conclusions

The healthcare sector has promoted the development of technologies for portable devices capable of remotely monitoring vital signs. The purpose of this development is to improve the efficiency and accessibility of healthcare services. To achieve this objective, the present study proposed a WD equipped with non-invasive sensors capable of monitoring critical health indicators in conjunction with machine learning algorithms. Among the various models examined, XGBoost exhibited the most superior predictive capabilities, attaining an R2 value of 0.9801. This model demonstrated low error metrics, including RMSE = 0.0383, MAE = 0.0014, and MAPE = 4.3478, while simultaneously attaining elevated classification values, such as F1-score ≈ 0.9985. These findings substantiate the model's capacity to predict intricate interrelationships among physiological variables and health parameters, including fever, tachycardia, and hypoxia.

The outcomes indicate that XGBoost outperforms the other evaluated models, which can be explained by its ensemble-based gradient boosting architecture that integrates multiple weak learners to effectively reduce both bias and variance. This approach allows the algorithm to model complex nonlinear interactions among physiological features, resulting in more precise predictions. In addition, XGBoost incorporates internal regularization techniques that mitigate overfitting, a crucial advantage when working with relatively small datasets. Given that the recorded physiological data are one-dimensional, XGBoost efficiently detects meaningful patterns without requiring extensive feature extraction. In contrast, CNN models tend to perform better with multidimensional data structures. Therefore, XGBoost provides an optimal compromise between computational efficiency and predictive reliability in the classification of physiological signals.

A comparison of these models with other existing models, such as CNN and SVM, revealed that they exhibited competitive performance. CNN demonstrated commendable classification performance, indicated by an accuracy of 0.9838, though it exhibited higher prediction errors, as evidenced by a MAPE of 15.94%. In contrast, the SVM model demonstrated comparable classification metrics to those of the XGBoost model Accuracy = 0.9955, though it exhibited modestly lower predictive capacity $R^2$ = 0.9405. The confusion matrices confirmed the high accuracy of all algorithms in identifying the "no condition" class. In addition, minor misclassifications appeared primarily between fever and tachycardia, highlighting potential areas for refinement in the models. The proposed WD demonstrates that combining wearable technology with advanced ML methods provides a low-cost, accurate, and accessible solution for continuous health monitoring. These findings demonstrate the potential of integrating ML into wearable systems to support early diagnosis and preventive intervention, paving the way for personalized healthcare strategies. Each portable wrist device costs approximately $50 to manufacture. Nevertheless, this cost could be reduced significantly through large-scale production. Reducing costs would increase accessibility and widespread use of this technology, as well as strengthen its viability as an economical alternative for comprehensive health monitoring programs. In addition, the price reduction resulting from mass production could drive its adoption in various fields, including public health projects and remote patient monitoring systems, thus expanding its impact on biomedical research and healthcare delivery.
The simultaneous monitoring of temperature, $SpO_2$, and heart rate has only recently appeared in the latest smartwatch models—such as the Google Pixel Watch 2, Apple Watch Series 9, Samsung Galaxy Watch 6, Garmin Vivoactive 5, and Huawei Watch GT-4—since earlier generations lacked at least one of these sensors, particularly temperature. Even in current devices, these features often lack a clear health-oriented application. In contrast, the wearable developed in this study was conceived from the outset as a low-cost, health-focused system designed specifically for continuous monitoring of temperature, oxygen saturation, and heart rate to support the early detection of fever, hypoxia, and tachycardia.

As future work, collaboration with the healthcare sector is proposed to validate the data obtained by the device and to implement its use for data collection in patients and individuals with potential health conditions. This includes conducting surveys to evaluate the possible application of the device in clinical contexts. Expanding the dataset aims to enhance the performance of the machine learning classification models and to explore new approaches for disease prediction based on vital signs. Furthermore, the integration of an inertial sensor is envisioned to support the prediction of conditions related to cardiovascular disorders, chronic diseases, stress, and anxiety. The combination of these sensors and analytical algorithms is expected to provide a more comprehensive framework for continuous monitoring, enabling early detection and facilitating preventive interventions. Additionally, the inclusion of diverse databases is considered to enrich the analysis and increase diagnostic accuracy. The implementation of these improvements has the potential to optimize the efficiency of healthcare systems and to provide advanced tools for personalized and proactive health management.

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