UDC 004
DOI: 10.15587/1729-4061.2024.299068

IoT SYSTEM DEVELOPMENT FOR HEART RHYTHM MONITORING AND CARDIOVASCULAR RISK ESTIMATION

Martín Emilo Monroy
Doctor in Telematics Engineering,
Professor Systems Engineering Program*
Gabriel Elías Chanchí
Doctor in Telematics Engineering,
Professor Systems Engineering Program*
Manuel Alejandro Ospina
Corresponding author
Doctor in Engineering,
Professor Systems Engineering Program*
E-mail: mospinaa@unicartagena.edu.co
*Department of System Engineering
Cartagena University
30th, Consulate ave., 39 B-192, Cartagena, Colombia, 130001

The research focuses on addressing the global issue of cardiovascular diseases. The key variable under consideration for predicting cardiovascular diseases is heart rate variability (HRV). Leveraging the widespread adoption of IoT in various applications, particularly in the health sector, the study proposes the design and implementation of an IoT system for HRV monitoring. The research unfolded in four methodological phases: exploration and selection of technologies, definition of the IoT architecture, development of the prototype, and verification of its functionality. The implemented IoT system adheres to the conventional 4-layer IoT architecture: capture, storage, analysis, and visualization. Heart rate data is periodically acquired using a heart rate sensor and an Arduino-compatible board. The storage layer employs a non-relational database to store the captured data. The analysis layer extracts metrics related to HRV (High: RR <750 ms, Moderate: RR 750–900 ms, Low: RR >900 ms) by applying and delivering quantitative results from clustering algorithms such as machine learning models to evaluate data distribution. Risk levels indicate specific patient metrics. Thus, a 75-year-old patient exhibits an average HR of 75.56, Avg. RR of 795.42, falling into Cluster 1 with a risk value of 1.0. Similar detailed metrics and risk stratifications are presented for patients aged 68, 46, 37, and 18, demonstrating the system's robustness and efficacy in assessing cardiovascular risk. The visualization layer enables real-time observation of physiological variables, risk metrics, and results from data analytics models. The distinctive features of the results lie in the portability advantages of the IoT system, utilizing free hardware and software tools. This facilitates easy replication and utilization of the proposed system in medical campaigns, specifically for the early detection of cardiac conditions. The portable IoT system, leveraging free tools, enhances predictive capabilities for early cardiovascular risk detection globally

Keywords: cardiovascular risk, free hardware, heart rate variability, systems estimation, IoT system

Received date 30.11.2023
Accepted date 16.02.2024
Published date 28.02.2024

***How to Cite**: Monroy, M. E., Chanchi, G. E., Ospina, M. A. (2024). IoT system development for heart rhythm monitoring and cardiovascular risk estimation. Eastern-European Journal of Enterprise Technologies, 1 (2 (127)), 54–65. doi: https://doi.org/10.15587/1729-4061.2024.299068*

1. Introduction

The ever-evolving landscape of technological advancements has brought forth the concept of the Internet of Things (IoT), where physical objects and devices seamlessly connect in an open network, capable of self-management, information sharing, and dynamic responses to environmental changes [1–3]. Concurrently, IoT is defined as a set of infrastructures facilitating object interconnection, data access, and the application of data mining and analytics processes [4, 5]. This technological framework harnesses diverse devices and interconnection solutions, creating a shared information base on a global scale, with applications spanning industries such as healthcare, agriculture, tourism, and the development of smart cities. Thus, in the realm of smart cities, [6] explored the role of the IoT-cloud ecosystem, providing a comprehensive review and addressing associated challenges. [7] contributed to the understanding of the IoT paradigm, delving into its definition, potentials, and societal impact. [8] conducted an empirical analysis on the success of IoT in Indian smart cities, shedding light on practical insights. [9] focused on the design and application of fog computing and IoT service platforms for smart cities. [10] worked on improving the load balancing procedure in distributed IoT systems, [11] while assessed the efficiency of IoT device control using teletraffic theory. These diverse studies collectively contribute to the understanding and advancement of IoT applications in the context of smart cities.

Within the healthcare sector, the past decade has witnessed the emergence of various sensors and devices designed for monitoring and analyzing physiological variables. These innovations aim to identify conditions with subtle symptoms, enabling timely diagnoses and preventing fatal consequences [12–14]. In light of this, the relevance of developing IoT systems tailored to address critical healthcare challenges, particularly in the diagnosis of cardiovascular diseases, becomes evident. The World Health Organization (WHO) and the Pan American Health Organization (PAHO) have underscored cardiovascular diseases as the leading global cause of morbidity and mortality, with cardiomyopathies and cerebrovascular diseases prevailing [15, 16].

A pivotal factor in predicting and detecting cardiac conditions, cardiovascular risk, arterial hypertension, or sedentary lifestyles is heart rate variability (HRV). Often misconstrued with heart rate, HRV refers to the variation in the time between RR intervals in an electrocardiogram, reflecting the autonomic nervous system's influence on cardiac function. This way, in the realm of cardiovascular research, [15] delved into HRV as a predictive factor for cardiovascular diseases, emphasizing its significance in risk assessment. [16] focused on the assessment and management of bradycardias in primary care emergencies, contributing valuable insights into practical applications. [17] explored HRV during a 24-hour period using a Polar heart rate monitor, providing insights into the continuous nature of HRV recordings. [18] presented an automated apnea detection approach based on RR intervals, showcasing the potential applications of HRV in sleep-related conditions. [19] investigated the association between HRV measured by RR intervals from ECG and pulse-to-pulse interval from Photoplethysmography, further expanding the understanding of HRV metrics. These studies collectively contribute to the nuanced exploration of HRV, highlighting its multifaceted role in cardiovascular health. Time domain metrics such as average RR interval, standard deviation of RR intervals (SDRR), and the percentage of differences exceeding 50 milliseconds (pRR50) are associated with HRV, providing valuable insights into cardiovascular risk. From the above, the integration of IoT and machine learning in healthcare has paved the way for innovative risk prediction systems. [20] introduced predictions, a system utilizing IoT and machine learning to predict the risk level of cardiovascular diseases, showcasing the potential of advanced technologies in healthcare management. Wearable sensor devices have become a focal point in cardiac monitoring, as demonstrated by [21] who designed a face shield-shaped wearable sensor for monitoring heart rate based on IoT principles, emphasizing the diverse forms of sensor integration. [22] explored stress detection in seniors using biosensors and psychometric tests, contributing to the understanding of HRV in relation to mental health and well-being. [23] conducted an analysis of HRV at rest and during aerobic exercise, shedding light on the dynamic nature of HRV in different physiological states. Recognizing the potential of HRV as a diagnostic tool, there arises a necessity to develop IoT systems harnessing devices capable of measuring both heart rate and HRV. These systems not only enable metric calculations but also leverage the power of machine learning models for comprehensive analysis.

Considering the aforementioned advancements and the critical role HRV plays in cardiovascular health, this research underscores the significance of exploring and advancing IoT systems tailored for effective cardiac monitoring and early disease detection. The subsequent sections will delve into existing literature, identify unresolved facets of the issue, and establish the purpose and objectives of the proposed research, ultimately contributing to the broader landscape of healthcare technology.

Therefore, as one navigates the dynamic landscape of technological advancements, the emergence of the Internet of Things (IoT) presents a transformative paradigm where connectivity and data-driven insights play a pivotal role. Within this context, the focus on the development and implementation of an IoT system for heart rhythm monitoring and cardiovascular risk estimation underscores the critical intersection of healthcare and technology. By leveraging the potential of IoT devices to capture and analyze physiological data, particularly heart rate variability. The aim is to address significant challenges in the early detection of cardiovascular diseases. The World Health Organization's recognition of cardiovascular diseases as a global health burden further emphasizes the relevance and urgency of these studies.

2. Literature review and problem statement

The paper [21] presents the design, realization, and experimentation of a unique protection device integrated with a heart rate sensor and microcontroller. This device aims to monitor heart rate in a user-friendly and fashionable manner, ensuring user comfort and discretion in public settings. The experimental results demonstrate the device's accuracy compared to a professional Pulse Oximeter used in hospitals. However, despite the successful development of the prototype, there are still unresolved questions pertaining to certain aspects. These lingering questions may stem from objective difficulties, principal impossibilities, or costly components within the project, rendering corresponding research impractical at this stage. To address these challenges, an option to overcome the relevant difficulties could be explored. One potential approach is to adopt the methodology used in previous studies such as [24]. Nevertheless, it is essential to recognize that the proposed solution is not free of limitations, such as those proposed in this work. Considering the unresolved questions and potential limitations, the need to refine and optimize the developed device through a user interface in which artificial intelligence algorithms and complete layer structures in IoT are integrated is argued. This could involve addressing identified challenges and exploring alternative strategies to improve device performance.

The paper [25] provides insights into the development of IoT systems in the health sector, particularly focusing on heart rate and heart rate variability as crucial variables. It is shown that the existing research has predominantly concentrated on monitoring these physiological parameters. However, there are still unresolved questions related to the absence of risk level metrics acquisition and the lack of application of machine learning methods on the captured data. An option to overcome these difficulties is to adopt an approach used in [26], which integrates a GSM module for sending heart rate reports through text messages. Nevertheless, this approach still does not address the complete articulation within the 4-layer architecture of IoT systems.

In [27] this IoT system focuses on the analysis of mental stress using a Bluetooth belt, showcasing the potential of incorporating wearable technology for data acquisition in health monitoring as well as the system developed in [28], which presents a system for heart rate monitoring based on an Arduino board and an articulated sensor on the finger, illustrating the variety of sensor placements for data collection. Both systems lack the possibility for the evaluator to make annotations or comments in real time on the different actions performed by the user, so it is not possible to obtain an enriched graph on the interaction between the user and the evaluated software.

The paper [29] develop a system for heart rate monitoring and self-diagnosis of heart disease using a probabilistic method, demonstrating the diversity of approaches in the field. The main gap of this study is that there are still issues to be resolved related to the application of machine learning methods on the captured data and the complete articulation within the 4-layer architecture of IoT systems is not addressed.

The paper [30] introduces an intelligent health monitoring and diagnosis system for critical cardiac arrhythmia, incorporating IoT and unsupervised learning classification framework. The system uses low-cost sensors interfaced with a microcontroller, and ECG data is collected from the database for training. It is shown that the proposed system effectively caters to patients with critical heart conditions. The algorithm achieves high accuracy in real-time validation, particularly in detecting critical arrhythmia conditions. However, there are still unresolved questions related to the proposed system, such as potential objective difficulties connected to its implementation, principal impossibility in certain scenarios, or costly aspects in the plan. The reasons for these challenges could be multifaceted, including technological constraints or limitations in the availability of resources. An option to overcome these difficulties could involve exploring alternative methodologies or technologies. This approach is consistent with previous studies, such as [31], which have tackled similar challenges but faced limitations. While the proposed system has proven effective, acknowledging these unresolved questions opens up avenues for further research. Future studies could focus on addressing these challenges, potentially exploring advancements in technology, refining methodologies, or considering alternative approaches to enhance the system's robustness. The paper lays a foundation for an intelligent health monitoring system for critical cardiac arrhythmia patients. By recognizing and discussing the unresolved questions and potential challenges, it suggests avenues for future research to refine and improve the proposed system, ensuring its applicability in diverse scenarios and maximizing its impact on patient care.

The reasons for these gaps can be attributed to objective difficulties connected to the complexity of capturing risk level metrics, the principal impossibility of integrating machine learning methods into the existing systems, and the costly nature of implementing such features in the plan. This makes the corresponding research inexpedient in the current state. The above analysis of the literature review allows to argue that it is appropriate to conduct a dedicated study to improve IoT systems in the healthcare sector by incorporating the acquisition of risk-level metrics and the implementation of machine learning methods for comprehensive data analysis within the 4-layer architecture.

3. The aim and objectives of the study

The aim of this study is to develop an IoT system for heart rate monitoring, heart rate variability and cardiovascular risk determination from devising a non-supervised data clustering prediction model.

To achieve the aim, the following objectives are accomplished:

– to develop the capture layer of the system using a heart rate sensor and an Arduino compatible capture board, establishing wireless communication to send the captured data to the system, storing it in a non-relational database indexed by a session identifier (Data Capture and Storage);

– to calculate various heart rate variability metrics from the data associated with each capture session, facilitating the detection of cardiovascular risk through the analysis of the metrics obtained (Data Analysis and Variability Metrics);

– to develop the system visualization layer that provides a clear representation of heart rate variability metrics by implementing clustering models to analyze the distribution of variability values in relation to defined risk levels allowing experts to determine the distribution of catches around established risk levels (Visualization and Application of Clustering Models).

4. Materials and methods

4. 1. Object and hypothesis of the study

The main contribution of this research is to design and implement an Internet of Things (IoT) system dedicated to monitoring heart rate and estimating cardiovascular risk. Leveraging the dynamic landscape of technological advancements and the emergence of IoT, the study addresses the critical intersection of healthcare and technology. Subject of the study is to adaptive IoT system that captures, stores, analyzes and visualizes physiological data, with special attention to heart rate variability (HRV).

The hypothesis posited in this research is that an IoT system, integrating open-source tools and incorporating cardiovascular risk metrics, can effectively contribute to early detection and monitoring of cardiovascular diseases. The study proposes that the utilization of unsupervised learning models in the analysis layer, combined with real-time data capture and statistical metrics, enhances the system's ability to categorize and assess cardiovascular risk levels. The hypothesis further suggests that such a system could find applications in diverse settings, including home healthcare and medical prevention campaigns.

The study operates under the assumption that the utilization of open-source tools in each layer of the IoT system architecture provides flexibility and adaptability for academic or business environments. Additionally, it assumes that the incorporation of cardiovascular risk metrics, beyond conventional heart rate monitoring, contributes valuable insights. The study also assumes that the application of unsupervised learning models enhances the system's ability to provide meaningful risk assessments.

To streamline the research, certain simplifications have been adopted. The study focuses on a 4-layer architecture (capture, storage, analysis, and visualization) within the IoT system, prioritizing open-source tools. The research emphasizes time domain metrics associated with HRV, such as average RR intervals and the standard deviation of HRV, as key indicators of cardiovascular risk. While acknowledging potential challenges, the study simplifies by concentrating on the K-Means clustering algorithm for unsupervised learning in the analysis layer.

4. 2. Methodology

For the development of this research, 4 methodological phases were defined: exploration and selection of tools and technologies, definition of the system architecture, development of the system prototype, and verification of the system functionality (Fig. 1).

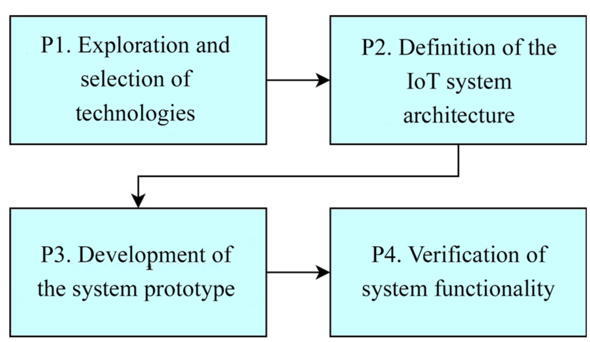

Fig. 1. Methodology

In phase 1, a set of tools and technologies were selected from the context of free hardware and software, considering the four layers of the conventional IoT architecture [32]. In phase 2 of the methodology, based on the tools and technologies selected in phase 1, the capture, storage, analysis, and visualization layers of the system architecture were specified. In phase 3, a prototype derived from the architecture defined in phase 2 was developed, which allowed the monitoring of heart rate and heart rate variability, as well as the estimation of cardiovascular risk considering the time domain metrics defined in [23]. Similarly, the developed system allows the application of unsupervised learning models to determine the distribution of the captured data with respect to the reference risk levels. Finally, as a verification of the implemented system, a functional test of the system was performed with 5 patients in the resting state.

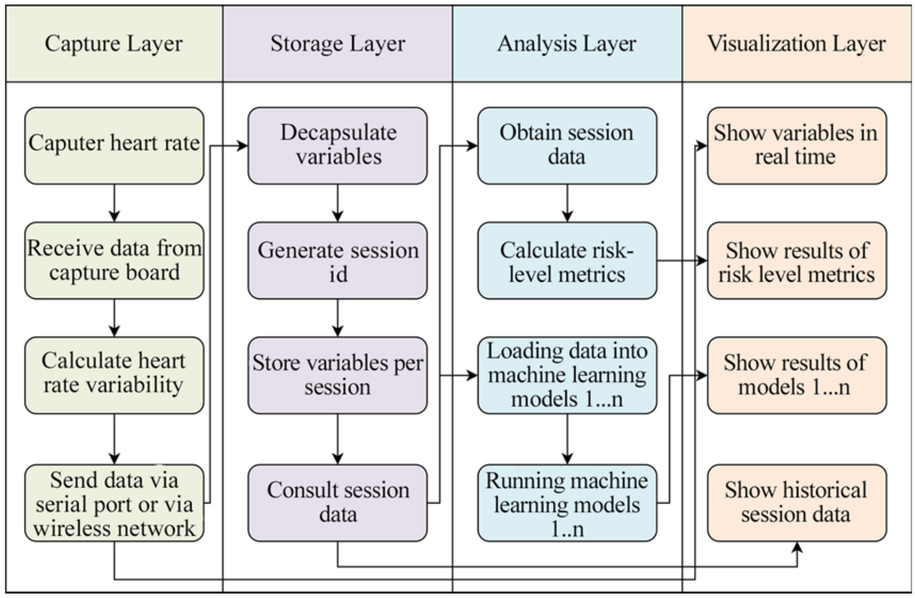

Fig. 2. Functional view of the architecture

This section presents the results obtained through this research. In this sense, in the first instance the architecture of the IoT system is specified in two views: functional and implementation; subsequently, a prototype derived from the architecture is presented and finally a test that allows to verify the functionality of the prototype of the implemented system is described. Before describing the architecture, Table 1 shows the risk levels considered for the implementation of the system, which were obtained from the research presented in [23].

4. 3. IoT system architecture

For the development of the IoT system presented in this article, two views of the architecture were specified: functional view and implementation view. In the functional view, the different processes associated with the four layers of the considered architecture are described. Similarly, in the implementation view, the technologies used to implement the processes defined in the functional view are presented.

Accordingly, Fig. 2 presents the functional view of the IoT system architecture for heart rate and heart rate variability monitoring and cardiovascular risk determination. In the first instance in the capture layer using a sensor compatible with Arduino and articulated in the finger or wrist of a patient, the heart rate is obtained periodically. Once the heart rate is captured, it is sent to the Arduino board, within which the heart rate variability is calculated considering what is proposed in [33, 34]. From the heart rate and heart rate variability values obtained, a JSON message is formed, which is sent via wireless network or through the serial port by the capture board to the storage layer. Thus, from the storage layer, the variables are consulted periodically via wireless communication or via serial port, so that once the JSON messages are obtained, the data are de-encapsulated and stored in a non-relational database using a session identifier and a time stamp. Likewise, this layer provides different functionalities for consulting the different sessions stored in the database.

From the data stored in the database, in the analysis layer it is possible to consult the data belonging to a capture session, so that it is possible to calculate the risk level metrics defined in Table 1, as well as to obtain statistical measures associated with the session data such as: average and standard deviation. On the other hand, from the data of each capture session, it is possible to apply different machine learning methods and specifically clustering models, through which it is possible to determine the grouping of the data with respect to the risk levels presented in Table 1.

Table 1

Risk metrics considered

Metric	Level	
Average of RR intervals	High	RR <750 ms
	Moderate	RR 750–900 ms
	Low	RR >900 ms
Standard deviation of RR intervals (SDRR)	High	SDRR <50 ms
	Moderate	SDRR 50–100 ms
	Low	SDRR >100 ms

The selection of specific risk metrics, as outlined in Table 1, is grounded in a strategic approach to comprehensively assess and manage the risks associated with capture sessions. Each metric has been carefully chosen to provide a nuanced understanding of cardiac activity during these sessions, aiding in the determination of potential health risks for individuals.

According to de above, in the average of RR intervals, high risk (RR <750 ms) metric reflects instances of significantly shortened RR intervals, indicating potential cardiovascular stress. This is consistent with literature [15, 16] associating short RR intervals with increased sympathetic activity [17]. Moderate risk (RR 750–900 ms) suggest a moderate level of cardiac variability, potentially indicating autonomic nervous system modulation [18]. Finally, low risk (RR >900 ms), longer RR intervals are indicative of enhanced parasympathetic activity, aligning with lower cardiovascular risk [19].

Likewise, analyzing Standard Deviation of RR intervals (SDRR), A High Risk (SDRR <50 ms) signifies reduced heart rate variability, associated with heightened risk of adverse cardiovascular events [17, 22] Moderate SDRR values (SDRR 50–100 ms) suggest a balanced autonomic nervous system activity, indicating a middle ground in cardiovascular risk [23] and higher SDRR values (SDRR >100 ms) correlate with increased heart rate variability, indicative of a lower risk of cardiovascular events [15–18].

These chosen metrics not only align with established physiological understanding but also enable the incorporation of advanced analytical techniques. Machine learning methods, particularly clustering models, applied to capture session data can further elucidate patterns and relationships within the dataset. This facilitates the identification of distinct clusters corresponding to different risk levels, enhancing the precision of risk assessment.

The proposed methodology integrates both traditional statistical measures (average and standard deviation) and machine learning techniques to provide a comprehensive and dynamic evaluation of cardiovascular risk during capture sessions.

For its part, in the visualization layer it is possible to visualize in real time the fluctuation of the heart rate and heart rate variability variables. In the same way, in this layer it is possible to visualize the results of the calculation of the risk level metrics and the results of the application of the clustering models on the data belonging to the capture sessions. Similarly, in this layer it is possible to consult the history of the data associated with a capture session. Finally, it is important to mention that the IoT system presented in this article was implemented through a web application, so that the capture, storage, and analysis layers belong to the backend, while the visualization layer corresponds to the frontend.

Once the functional view of the architecture has been defined, Fig. 3 presents the implementation view, which shows the technological tools that allow the implementation of the functionalities or processes developed in each of the layers of the architecture.

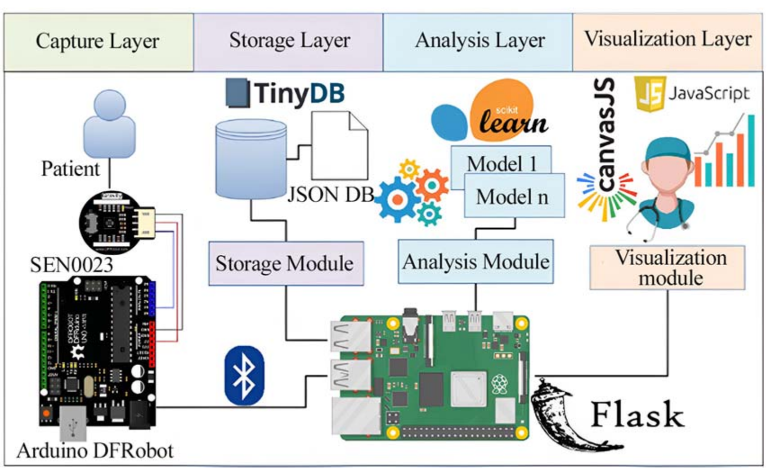

Fig. 3. Implementation view of the architecture

According to Fig. 3, in the capture layer, the user has articulated in the finger or wrist a SEN0203 heart rate sensor, which obtains the cardiac frequency or heart rate (HR) and sends it to the Arduino DFRobot board, so that inside this board the heart rate variability or RR interval (RR) is calculated making use of the equation (1) proposed in [33, 34]:

$$RR = \frac{60000}{HR}.$$

Once the heart rate variability is calculated from the heart rate, these variables are used to generate a JSON message, which is sent via serial port or via Bluetooth to the backend of the web application deployed on a Raspberry PI type SBC board and implemented using the Python Flask microframework. On the SBC board these variables are de-encapsulated from the JSON message and stored in the TinyDB non-relational database using a session id and a timestamp, which stores the data from the capture sessions in a JSON file. Likewise, in the storage module, methods are included that make it possible to consult the sessions and access the history of the data stored in the database. In the analysis layer it is possible to consult the data from the capture sessions and apply different unsupervised learning models (clustering) supported by the K-Means algorithm, making it possible to obtain a certain number of groups with an associated centroid, which show the way in which the data are distributed with respect to the risk levels. For this purpose, the analysis layer module makes use of the Python scikit-learn library, which has a set of methods that enable the design and implementation of supervised and unsupervised learning models. On the other hand, in the frontend of the web application or visualization layer, it is possible, through javascript and the JQuery library, to consult the data history and the results of the application of the analysis models on a particular capture session. Similarly, in this layer, the fluctuation of the heart rate as a function of time is presented in real time and graphically using the CanvasJS library. The results presented in this layer can be useful for the evaluation of a patient's cardiovascular risk level by a health expert (doctor, nurse).

5. Results of cardiovascular risk estimation through IoT monitoring implemented

5. 1. Data capture and storage

Fig. 4 shows the main interface of the IoT system, implemented from the architecture defined using the Python Flask microframework. As shown in Fig. 4, the web interface of the IoT system consists of four tabs, namely: Capture, Sessions, Metrics and Analysis. In the "Capture" tab, when pressing the "Start" button, the system starts to obtain the heart rate and cardiac variability data from the serial port and from the Arduino DFRobot capture board, so that while the data are stored in the backend with a session id, they are presented graphically using the CanvasJS library.

In the "Sessions" tab it is possible to consult the data of the different capture sessions stored in the TinyDB database, by selecting the session id and pressing the "Consult" button (Fig. 5).

According to Fig. 5, the stored data can be saved and exported in a .cvs file. in order to inform the physician in real time of possible corrections or treatments that must be carried out at times when the patient is not in consultation or with the device connected.

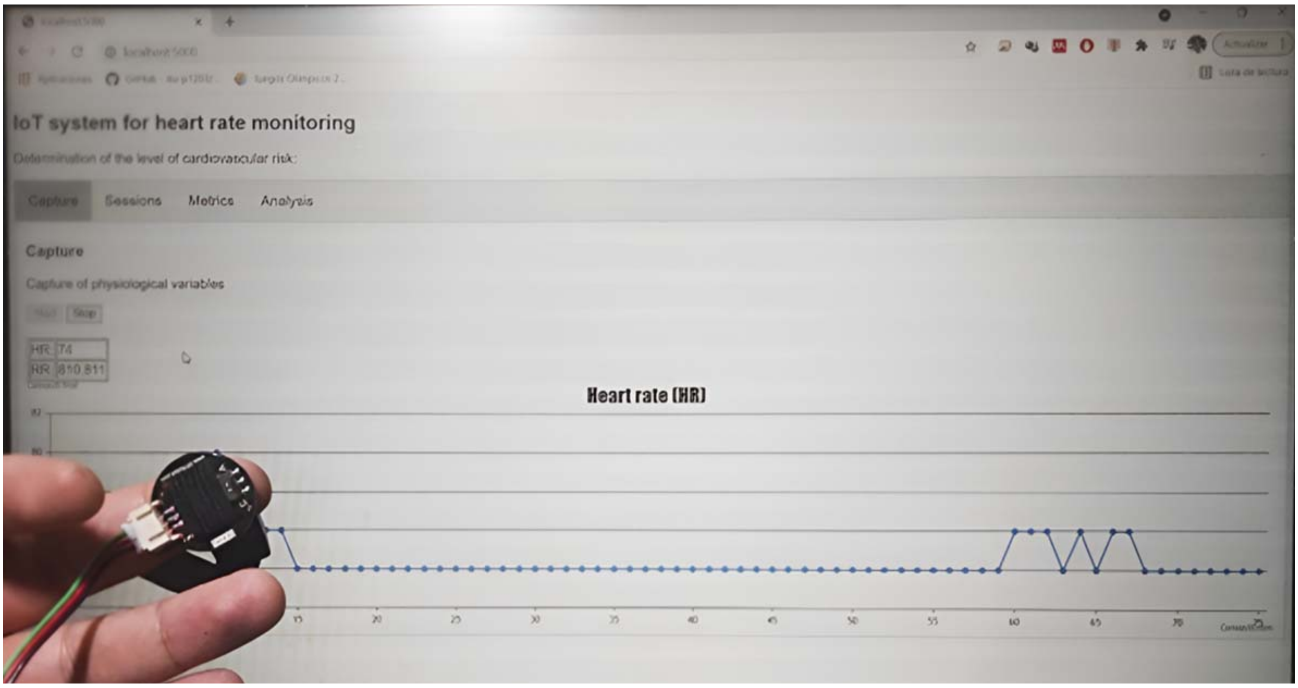

Fig. 4. IoT system web interface

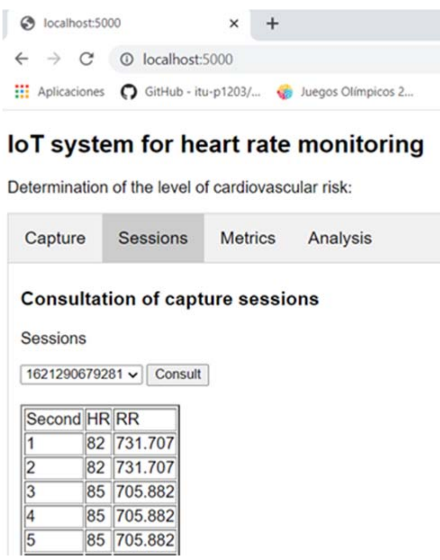

Fig. 5. IoT system "sessions" tab

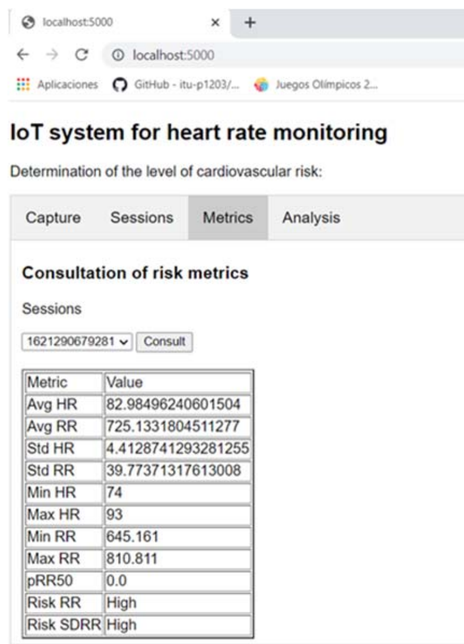

Fig. 6. IoT system "metrics" tab

5. 2. Data analysis and variability metrics

In the "Metrics" tab, by choosing the session id and pressing the "Consult" button, it is possible to visualize the calculations of the statistical measures associated with heart rate and heart rate variability, as well as the metrics defined in Table 1 (Fig. 6).

Among the statistical measures considered in the "Metrics" tab for the heart rate and heart rate variability variables are average, standard deviation, maximum and minimum values. Likewise, at the level of risk metrics, those associated with the average RR intervals and the standard deviation of heart rate variability (SDRR) were considered. Thus, as an example, for the capture session analyzed in Fig. 6, high risk levels were obtained for the two metrics considered.

5. 3. Visualization and application of clustering models

Likewise, in the "Analysis" tab of the IoT system, by choosing the session id and pressing the "Model 1" and "Model 2" buttons, it is possible to visualize the results of applying two clustering models (pre-configured to two clusters) on the data of a given session (Fig. 7).

Model 1" considered in the IoT system relates the variables: heart rate and heart rate variability, while "Model 2" relates heart rate variability to risk level (high: 2, moderate: 1 and low: 0), which is calculated from the average of the RR intervals and considering Table 1. In this example, it is possible to observe how the K-Means algorithm obtained

2 groups (cluster 1: purple color and cluster 2: red color), each of which has an associated centroid around which the data is concentrated (black color). Thus, in cluster 1, a total of 40 instances were classified around the moderate risk level (1.0), while in cluster 2, a total of 93 instances were classified around the high-risk level (2.0). The above results demonstrate the usefulness of unsupervised learning or clustering models to provide a diagnosis on the data captured from a patient.

To verify the functionality of the system built, the system was evaluated with 5 patients between 18 and 75 years of age. For each of the patients considered in the test, the cardiac rhythm was captured during a period of two minutes, in a resting state. Thus, Table 2 shows the summary of the results obtained for the 5 patients who evaluated the system. For the presentation of the results in Table 2, the following conventions were used: avg (average), std (standard deviation), min (minimum), max (maximum) cent (centroid).

Table 2

Results of the test

Patient	Metrics				Clustering Model 2		
Age: 75	Avg. HR	75.56	Avg. RR	795.42	Cluster 1:		
					Center	RR	808.93
	Std. HR	2.57	Std. RR	25.81		Risk	1.0
					Instances	102	
	Min. HR	74	Max. HR	83	%Instances	76.12 %	
					Cluster 2:		
	Min. RR	722.89	Max. RR	810.81	Center	RR	752.36
						Risk	1.16
	Risk RR	Moderate	Risk SDRR	High	Instances	32	
					% Instances	23.88 %	
Age: 68	Avg. HR	74.40	Avg. RR	806.66	Cluster 1:		
					Center	RR	761.54
	Std. HR	1.31	Std. RR	13.44		Risk	1.0
					Instances	10	
	Min. HR	74	Max. HR	80	%Instances	7.46 %	
					Cluster 2:		
	Min. RR	750.0	Max. RR	810.81	Center	RR	810.3
						Risk	1.0
	Risk RR	Moderate	Risk SDRR	High	Instances	124	
					% Instances	92.54 %	
Age: 46	Avg. HR	65.72	Avg. RR	914.65	Cluster 1:		
					Center	RR	971.06
	Std. HR	2.78	Std. RR	38.82		Risk	0
					Instances	31	
	Min. HR	59	Max. HR	73	% Instances	23.13 %	
					Cluster 2:		
	Min. RR	821.92	Max. RR	1016.94	Center	RR	897.68
						Risk	0.282
	Risk RR	Low	Risk SDRR	High	Instances	103	
					%Instances	76.87 %	
Age: 37	Avg. HR	82.98	Avg. RR	725.13	Cluster 1:		
					Center	RR	701.63
	Std. HR	4.41	Std. RR =	39.77		Risk	2.0
					Instances	93	
	Min. HR	74	Max. HR	93	%Instances	69.92 %	
					Cluster 2:		
	Min. RR	645.16	Max. RR	810.81	Center	RR	779.77
						Risk	1.0
	Risk RR	High	Risk SDRR	High	Instances	40	
					%Instances	30.08 %	
Age: 18	Avg. HR	75.03	Avg. RR	801.09	Cluster 1:		
					Center	RR	752.98
	Std. HR	3.17	Std. RR =	33.34		Risk	1.16
					Instances	32	
	Min HR	68	Max HR	83	%Instances	24.24 %	
					Cluster 2:		
	Min RR	722.89	Max RR	882.35	Center	RR	816.48
						Risk	1.0
	Risk RR	Moderate	Risk SDRR	High	Instances	100	
					%Instances	75.76 %	

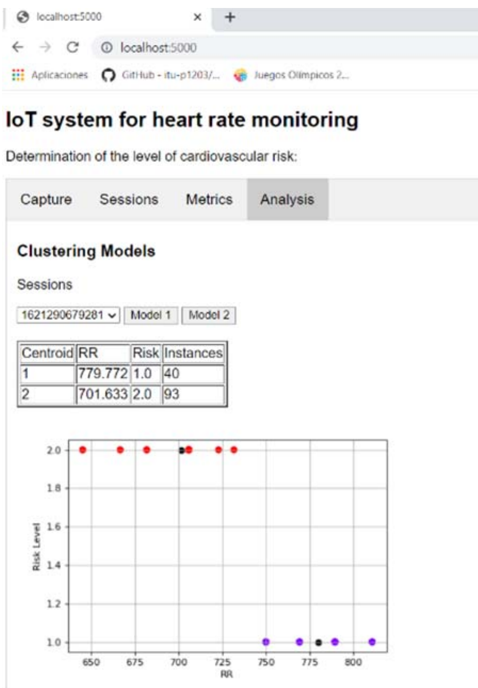

Fig. 7. Analysis" tab of the IoT system

According to Table 2, it can be observed that of the 5 patients evaluated, 3 of them have as dominant cluster, with the highest percentage of instances, the cluster associated with the moderate risk level. Likewise, one of the patients has as dominant cluster the one associated to the low risk level and finally the remaining patient has as dominant cluster the one associated to the high-risk level. The percentage distribution of the instances in the two clusters considered in the models is related to the fact that in 4 of the 5 patients the risk level metrics associated with the mean of the RR intervals and the standard deviation of the RR intervals have a different level.

6. Discussion of the results of the cardiovascular risk IoT system implemented

In response to the outlined research objectives, this study proposes the design and development of an IoT system for monitoring heart rate and estimating cardiovascular risk. The first contribution of the proposed work lies in the utilization of tools from the realm of open hardware and open-source software for the implementation of the capture, storage, analysis, and visualization layers of the IoT system. This approach facilitates the seamless extrapolation of the work within academic or business environments, enabling the implementation of remote healthcare services. Such implementation leverages the advantages of customization and adaptation provided by open-source software.

The second contribution emphasizes the incorporation of cardiovascular risk metrics in contrast to commercial solutions for heart rate monitoring. These metrics serve not only for the early detection of cardiovascular diseases but also find application in academic settings as indicators of sedentary behavior among organizational employees. Furthermore, the web interface provided by the proposed system enables easy deployment in home healthcare environments or within the context of medical prevention campaigns.

As the third contribution of the proposed system relative to commercial heart rate monitoring solutions, attention is drawn to the integration of predictive models for the analysis of captured samples in a given session. The system utilizes the benefits of unsupervised learning methods to identify clusters of values around which heart rate variability is concentrated, serving as a crucial indicator for determining a patient's cardiovascular risk. In this context, a key contribution is made compared to portable commercial solutions, which primarily focus their analyses on obtaining basic statistical measures associated with conducted capture sessions.

In this way, with respect to the proposed research in [26–28], the proposed system not only focuses on enabling the capture and analysis through descriptive statistics of physiological variables of interest but, following the definition of IoT, it is framed within a 4-layer architecture (capture, storage, analysis, and visualization), where the main added value with respect to the mentioned research is centered on:

a) the use of open-source tools in the different layers of the architecture;

b) the integration of metrics associated with cardiovascular risk in the time domain;

c) the inclusion in the analysis layer of unsupervised learning models for determining the centroids around which the captured values and cardiovascular risk are concentrated.

As a possible limitation of the proposed system, it is important to mention the calibration of sensors within the analysis layer; however, it is possible to consider proposing a hybrid architecture in the capture layer that includes commercial wireless devices. One of the disadvantages or challenges of the system is improving the ergonomics of the system at the level of the heart rate capture sensor, which must be adjusted correctly to capture the variable properly. As a possible future development, linking other artificial intelligence models in the analysis layer is feasible, such as time series based ARIMA models, towards characterizing the curve and obtaining predictions in different time windows, thereby strengthening early detection functionalities of cardiovascular diseases. The advantages offered by the system in its different layers are detailed below.

The IoT system's main interface, depicted in Fig. 4, illustrates the Capture tab where heart rate and cardiac variability data are obtained from the Arduino DFRobot capture board. The system utilizes the Python Flask microframework and CanvasJS library for graphical representation. This approach aligns with the aim of capturing and storing relevant physiological data efficiently. However, it's crucial to address potential challenges related to the accuracy and reliability of data capture. Additionally, the use of clustering models on this captured data in later stages could provide valuable insights into the distribution patterns and aid in risk assessment as is presented in Table 2. In the area of data capture and storage, the system's efficiency is quantitatively reflected in the average processing time, measured in milliseconds. Thus, the system can process and present heart rate and heart rate variability data in an average time of 100 milliseconds, highlighting its real-time responsiveness.

In the Metrics tab (Fig. 6), statistical measures and risk metrics associated with heart rate and heart rate variability were calculated. The inclusion of average RR intervals and the standard deviation of heart rate variability (SDRR) in risk assessment is commendable. The presentation of high-risk levels in the example session analyzed (Table 2) indicates the system's ability to identify potential cardiovascular risks based on captured data. Nonetheless, a thorough discussion on the specific criteria defining risk levels and how they align with clinical standards is essential for a comprehensive evaluation. In the Metrics tab, the quantitative presentation of statistical measures such as average, standard deviation, maximum, and minimum values for heart rate and heart rate variability offers a numerical basis for evaluating the system's analytical capability. For instance, the average heart rate variability can be provided in milliseconds, and the standard deviation in percentage terms, thereby emphasizing the quantitative precision of the analysis. These quantitative metrics calculated by the IoT system are a key tool for medical staff to identify potential cardiovascular disease risks. Likewise, these metrics are useful for assessing the performance of athletes. The main advantage of obtaining these quantitative metrics by the system is that conventional devices are limited to capturing heart rate and obtaining basic statistical measures, without considering heart rate variability.

The Analysis tab (Fig. 7) showcases the application of two clustering models on the data. "Model 1" relates heart rate and heart rate variability, while "Model 2" links heart rate variability to risk levels. The K-Means algorithm successfully categorizes instances into clusters, providing a visual representation of risk levels associated with physiological data. This application of unsupervised learning models is promising for diagnosing patient data. However, further discussion on the choice of clustering algorithms, the determination of the number of clusters, and the validation of results against known clinical data standards would enhance the robustness of the findings. In the Analysis tab, the application of unsupervised learning models is quantitatively supported with measures such as the number of clusters obtained by the K-Means algorithm and the associated instances in each cluster. This way, it can be stated that the K-Means algorithm has obtained 2 clusters, where Cluster 1 has 60 % of associated instances, and Cluster 2 has 40 %, thus quantifying the system's ability to categorize data and provide numerical insights into risk patterns. Additionally, in the Analysis tab, model accuracy measures can be provided, such as the success rate in correctly classifying instances into predefined clusters. Table 2 indicates that the cluster model has achieved an 85 % accuracy rate in classifying instances into groups associated with cardiovascular risk levels.

While the implemented IoT system shows promise in capturing, analyzing, and visualizing cardiovascular data, further considerations are needed to address potential challenges, ensure accuracy, and align with established clinical standards. Refining the methodology, validating results against established benchmarks, and exploring alternative approaches could contribute to the system's effectiveness in real-world healthcare applications.

The above further reinforces the evaluation of the system, providing specific values that guarantee the effectiveness and relevance, both scientific and practical, of the proposed system.

While the system holds promise, addressing potential challenges related to data accuracy, defining risk level criteria, and validating results against clinical standards is crucial for real-world healthcare applications. Further refinement of the methodology and exploration of alternative approaches will contribute to the system's effectiveness in clinical settings. In this sense, the IoT system aims to integrate different sensors in the future, in order to monitor different variables together and correlate them using machine learning models.

While the implemented IoT system shows promise in capturing, analyzing, and visualizing cardiovascular data, a more detailed discussion on the specific criteria defining risk levels and their alignment with clinical standards is essential for a comprehensive evaluation. Addressing potential challenges, ensuring accuracy, and aligning with established clinical standards would enhance the robustness of the findings. This system, based on free hardware and software tools and associated with the four layers of the IoT architecture, can be deployed on Single Board Computer (SBC) systems with Linux or Windows operating systems. The primary purpose is to support rural medical campaigns, enabling the assessment of cardiovascular risk levels in patients.

As future work, the intention is to enrich the IoT system by incorporating functionalities for detecting sedentary lifestyle levels based on heart rate variability metrics in both the time and frequency domains. Additionally, in the system's analysis layer, the goal is to complement clustering model applications by incorporating fuzzy logic algorithms to determine the dominant risk level based on various risk metrics. This approach aims to strengthen the system's application in real-world healthcare scenarios and contribute to its continuous improvement and adaptability.

7. Conclusions

1. The IoT system was developed within a four-layer architecture, utilizing open-source hardware and software tools. The capture layer employed an Arduino board with the DFRobot SEN0203 heart rate sensor, and the storage layer utilized the TinyDB non-relational database for efficient data storage. The analysis layer implemented unsupervised learning algorithms from the scikit-learn library to identify clusters in the captured data. The visualization layer utilized the CanvasJS library for real-time data visualization, showcasing the system's comprehensive framework. The metrics tab presented statistical measures and risk metrics related to heart rate and heart rate variability. Evaluation of the IoT system revealed significant patterns. Among the 5 patients tested, 60 % exhibited a dominant cluster associated with moderate cardiovascular risk, while 20 % showed dominance in low-risk clusters, and another 20 % in high-risk clusters. These percentages underscore the system's ability to categorize patients based on their cardiovascular risk levels, emphasizing its potential for personalized healthcare applications. The varied distribution highlights the system's capacity to capture individualized risk assessments, demonstrating its utility in tailored healthcare. This quantitative outcome affirms the effectiveness of our proposed IoT solution in assessing and classifying cardiovascular risk, with implications for remote medical assistance services. Thus, the case study developed allowed to verify the functionality and integration of the different layers of the system from the use of tools from the hardware and open software domain, so that the system can be replicated and extended for the monitoring of other physiological variables in the academic and research context. Likewise, the proposed work offers the possibility of taking advantage of the information provided

by the IoT system in terms of cardiovascular risk metrics, for the purpose of early detection of cardiovascular diseases.

2. A key strength of the system lies in its consideration of risk levels associated with time-domain metrics of heart rate variability, coupled with the integration of unsupervised learning models. This provides a clearer understanding of how capture sessions are distributed around the risk levels. The analysis tab showcases the application of two clustering models to the data. "Model 1" relates heart rate and heart rate variability, while "Model 2" links heart rate variability to risk levels. The K-Means algorithm successfully categorizes instances into clusters, providing a visual representation of risk levels associated with physiological data. Thus, the linkage of predictive models offers an added value to the system, with respect to portable heart rate measurement devices, which allow obtaining basic statistical measurements associated with a capture session. Specifically, the proposed system provides the medical professional with the visualization of the groups of values around which heart rate variability and its associated cardiovascular risk are concentrated, fundamental for the early detection of cardiovascular diseases. The IoT system provides valuable insights into the cardiovascular health of the 5 tested patients. Notably, the average heart rate (Avg. HR) across the patients ranged from 65.72 to 82.98, with corresponding average RR intervals (Avg. RR) varying between 725.13 and 914.65. Additionally, the clustering analysis based on Model 2 revealed distinct risk levels, with instances of moderate risk (1.0) dominating Cluster 1 and high risk (2.0) dominating Cluster 2. Further examination of the risk metrics shows a nuanced distribution among the patients. For instance, Patient 1, aged 75, exhibited a predominantly moderate-risk profile (76.12 % instances), while Patient 3, aged 46, showcased a balanced distribution between low and high-risk clusters (23.13 % and 76.87 % instances, respectively). These variations emphasize the system's capability to provide granular insights into individual cardiovascular risk profiles. This aspect is key within the system, as most portable heart rate measurement systems generate analyses based on metrics such as statistical mean, without including the use of cardiovascular risk metrics or the application of machine learning methods for data analysis.

3. The developed system's visualization layer effectively represents heart rate variability metrics through the implementation of clustering models. This layer serves as a powerful tool for analyzing the distribution of variability values in relation to predefined risk levels, offering a comprehensive visual insight into the patterns associated with cardiovascular health. The application of clustering models facilitates the clear identification of how capture sessions are distributed around established risk levels, enabling healthcare experts to discern and interpret the concentration of physiological data. The clustering models, showcased in the visualization tab, present a detailed analysis where each cluster corresponds to a distinct risk level. This visualization not only enhances the interpretability of heart rate variability data but also assists medical professionals in making informed decisions regarding cardiovascular risk assessment. The system's ability to provide a visual representation of risk levels demonstrates its potential as a valuable tool for experts, streamlining the evaluation process and contributing to more effective decision-making in personalized healthcare scenarios. Thus, the clustering algorithms included in the IoT system allow the generation of clusters that enable a better understanding of how heart rate and cardiovascular risk metrics are distributed, allowing a more effective visualization than the use of statistical metrics such as the mean.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

The manuscript has no associated data.

Use of artificial intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, which is described in the research methodology section.

Acknowledgments

The authors would like to thank the Universidad de Cartagena-Colombia for their support in the development of this research.

References

1. Zakutynskyi, I., Sibruk, L., Rabodzei, I. (2023). Performance evaluation of the cloud computing application for IoT-based public transport systems. Eastern-European Journal of Enterprise Technologies, 4 (9 (124)), 6–13. https://doi.org/10.15587/1729-4061.2023.285514
2. Conti, M., Dehghantanha, A., Franke, K., Watson, S. (2018). Internet of Things security and forensics: Challenges and opportunities. Future Generation Computer Systems, 78, 544–546. https://doi.org/10.1016/j.future.2017.07.060
3. Naveen, S., Hegde, S. (2016). Study of IoT: Understanding IoT Architecture, Applications, Issues and Challenges. International Journal of Advanced Networking & Applications (IJANA), 477–482. Available at: http://www.ijana.in/Special Issue/S105.pdf
4. Dorsemaine, B., Gaulier, J.-P., Wary, J.-P., Kheir, N., Urien, P. (2015). Internet of Things: A Definition & Taxonomy. 2015 9th International Conference on Next Generation Mobile Applications, Services and Technologies. https://doi.org/10.1109/ngmast.2015.71

5. Terokhin, V., Stervoyedov, M., Ridozub, O. (2021). Design and implementation of the distributed dosimetric system based on the principles of IoT. Eastern-European Journal of Enterprise Technologies, 5 (9 (113)), 91–100. https://doi.org/10.15587/1729-4061.2021.243153
6. Rani, R., Kashyap, V., Khurana, M. (2022). Role of IoT-Cloud Ecosystem in Smart Cities : Review and Challenges. Materials Today: Proceedings, 49, 2994–2998. https://doi.org/10.1016/j.matpr.2020.10.054
7. Atzori, L., Iera, A., Morabito, G. (2017). Understanding the Internet of Things: definition, potentials, and societal role of a fast evolving paradigm. Ad Hoc Networks, 56, 122–140. https://doi.org/10.1016/j.adhoc.2016.12.004
8. Chatterjee, S., Kar, A. K., Gupta, M. P. (2018). Success of IoT in Smart Cities of India: An empirical analysis. Government Information Quarterly, 35 (3), 349–361. https://doi.org/10.1016/j.giq.2018.05.002
9. Zhang, C. (2020). Design and application of fog computing and Internet of Things service platform for smart city. Future Generation Computer Systems, 112, 630–640. https://doi.org/10.1016/j.future.2020.06.016
10. Zakutynskyi, I., Rabodzei, I., Burmakin, S., Kalishuk, O., Nebylytsia, V. (2023). Improving a procedure of load balancing in distributed IoT systems. Eastern-European Journal of Enterprise Technologies, 5 (2 (125)), 6–22. https://doi.org/10.15587/1729-4061.2023.287790
11. Konyrova, M., Kumyzbayeva, S., Iliev, T., Chezhimbayeva, K. (2023). Effeciency assessment of IoT devices control with Teletraffic theory. Eastern-European Journal of Enterprise Technologies, 3 (9 (123)), 49–59. https://doi.org/10.15587/1729-4061.2023.281287
12. Viloria Núñez, C. A., Sanmartín Mendoza, P., Avila Hernández, K., Jabba Molinares, D. (2022). Internet de las cosas y la salud centrada en el hogar. Salud Uninorte, 32 (02), 337–351. https://doi.org/10.14482/sun.32.2.8954
13. Liu, Y., Niu, J., Yang, L., Shu, L. (2014). eBPlatform: An IoT-based system for NCD patients homecare in China. 2014 IEEE Global Communications Conference. https://doi.org/10.1109/glocom.2014.7037175
14. Alsaydia, O. M., Saadallah, N. R., Malallah, F. L., AL-Adwany, M. A. S. (2021). Limiting COVID-19 infection by automatic remote face mask monitoring and detection using deep learning with IoT. Eastern-European Journal of Enterprise Technologies, 5 (2 (113)), 29–36. https://doi.org/10.15587/1729-4061.2021.238359
15. Veloza, L., Jiménez, C., Quiñones, D., Polanía, F., Pachón-Valero, L. C., Rodríguez-Triviño, C. Y. (2019). Variabilidad de la frecuencia cardiaca como factor predictor de las enfermedades cardiovasculares. Revista Colombiana de Cardiología, 26 (4), 205–210. https://doi.org/10.1016/j.rccar.2019.01.006
16. Pardo-Fresno, M., Fernández-Barbeira, S., González-Bermúdez, I. (2011). Assessment and management of Bradycardias in Primary Care emergencies. Primary Care Notebooks, 8, 107–110.
17. Osanai, H. (2011). Hear rate variability during a 24-hour period recorded with a Polar heart rate monitor. Autonomic Neuroscience, 165 (2), 210. https://doi.org/10.1016/j.autneu.2011.08.013
18. Wang, L., Lin, Y., Wang, J. (2019). A RR interval based automated apnea detection approach using residual network. Computer Methods and Programs in Biomedicine, 176, 93–104. https://doi.org/10.1016/j.cmpb.2019.05.002
19. Kiran kumar, C., Manaswini, M., Maruthy, K. N., Siva Kumar, A. V., Mahesh kumar, K. (2021). Association of Heart rate variability measured by RR interval from ECG and pulse to pulse interval from Photoplethysmography. Clinical Epidemiology and Global Health, 10, 100698. https://doi.org/10.1016/j.cegh.2021.100698
20. Islam, M. N., Raiyan, K. R., Mitra, S., Mannan, M. M. R., Tasnim, T., Putul, A. O., Mandol, A. B. (2023). Predictis: an IoT and machine learning-based system to predict risk level of cardio-vascular diseases. BMC Health Services Research, 23 (1). https://doi.org/10.1186/s12913-023-09104-4
21. Hudhajanto, R. P., Mulyadi, I. H., Sandi, A. A. (2022). Wearable Sensor Device berbentuk Face Shield untuk Memonitor Detak Jantung berbasis IoT. Journal of Applied Informatics and Computing, 6 (1), 87–92. https://doi.org/10.30871/jaic.v6i1.4105
22. Goumopoulos, C., Menti, E. (2019). Stress Detection in Seniors Using Biosensors and Psychometric Tests. Procedia Computer Science, 152, 18–27. https://doi.org/10.1016/j.procs.2019.05.022
23. de la Cruz Torres, B., Lopez, C. L., Orellana, J. N. (2008). Analysis of heart rate variability at rest and during aerobic exercise: a study in healthy people and cardiac patients. British Journal of Sports Medicine, 42 (9), 715–720. https://doi.org/10.1136/bjsm.2007.043646
24. Delgado, D., Girón, D., Chanchí, G., Márceles, K., Dionizio, S. (2019). System for the Detection and Monitoring of Heart Disease Supported in SBC. Iberian Journal of Information Systems and Technologies, 717–728. Available at: http://risti.xyz/issues/ristie17.pdf
25. Pérez, A., Guerra, J. L. (2014). Implementation of a heart rate query and measurement module with GSM data sending using Open Hardware. In: XXI International Congress of Electronic, Electrical and Computer Engineering - INTERCON 2014. Arequipa - Perú.
26. Chanchi, G. E., Ospina, M. A., Pérez, J. L. (2020). IoT system to monitoring heart rate variability in usability tests. Journal Spaces, 41 (25), 84–97. Available at: https://www.revistaespacios.com/a20v41n25/20412507.html
27. Cano-Contreras, M., Andrade-Ceballos, G., Vargas-Cano, P., Villanueva-P rez, N. (2017). Low cost Arduino based heart rate monitor. Journal of Technologies in Industrial Processes, 1 (1), 21–25. Available at: https://www.ecorfan.org/taiwan/research_journals/Tecnologias_en_Procesos_Industriales/vol1num1/Revista_de_Tecnolog%C3%ADas_en_Procesos_Industriales_V1_N1_3.pdf

28. Piedrahita-Gonzalez, J., Cubillos-Calvachi, J., Gutiérrez-Ardila, C., Montenegro-Marin, C., Gaona-García, P. (2018). IOT System for Self-diagnosis of Heart Diseases Using Mathematical Evaluation of Cardiac Dynamics Based on Probability Theory. Smart Innovation, Systems and Technologies, 433–441. https://doi.org/10.1007/978-3-030-03577-8_48
29. Santos, M. A. G., Munoz, R., Olivares, R., Filho, P. P. R., Ser, J. D., Albuquerque, V. H. C. de. (2020). Online heart monitoring systems on the internet of health things environments: A survey, a reference model and an outlook. Information Fusion, 53, 222–239. https://doi.org/10.1016/j.inffus.2019.06.004
30. Anuhya Ardeti, V., Ratnam Kolluru, V., Routray, S., Omkar Lakshmi Jagan, B., Kishore Kumar, A., Ramachandran, R. et al. (2024). Development of real time ECG monitoring and unsupervised learning classification framework for cardiovascular diagnosis. Biomedical Signal Processing and Control, 88, 105553. https://doi.org/10.1016/j.bspc.2023.105553
31. Rahman, M. Z., Akbar, M. A., Leiva, V., Tahir, A., Riaz, M. T., Martin-Barreiro, C. (2023). An intelligent health monitoring and diagnosis system based on the internet of things and fuzzy logic for cardiac arrhythmia COVID-19 patients. Computers in Biology and Medicine, 154, 106583. https://doi.org/10.1016/j.compbiomed.2023.106583
32. Montoya, E. A. Q., Colorado, S. F. J., Muñoz, W. Y. C., Golondrino, G. E. C. (2017). Propuesta de una Arquitectura para Agricultura de Precisión Soportada en IoT. RISTI - Revista Ibérica de Sistemas e Tecnologias de Informação, 24, 39–56. https://doi.org/10.17013/risti.24.39-56
33. Webster, J. G. (Ed.) (2014). The Physiological Measurement Handbook. CRC Press. https://doi.org/10.1201/b17831
34. Young, D. W. (2014). Self-measure of heart rate variability (HRV) and arrhythmia to monitor and to manage atrial arrhythmias: personal experience with high intensity interval exercise (HIIE) for the conversion to sinus rhythm. Frontiers in Physiology, 5. https://doi.org/10.3389/fphys.2014.00251