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eHeart-BP, Prototype of the Internet of Things to Monitor Blood Pressure

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Abstract— **The Internet of Things paradigm has a wide range of scenarios that capture information of different nature and essentially make communication easier. Sensing is one of the most interesting scenarios by making possible to perform biometric measurements. This allows the supporting of relevant decisions related to the health and well-being of individuals, besides, biometric measurements can be performed and being reported in real time to experts in the health area. Providing a path to timely preventive healthcare.**

The main biometric parameter of interest in this paper is blood pressure (BP), which is related with the high rates of death in Colombia and the world cause by arterial hypertension. This could be prevented by its timely measurement and systematic monitoring. Nevertheless, it is notorious the absence of a practical gadget or methodology that satisfies the requirements focus on a portable and comfortable BP monitoring system. The objective of this research is the design and development of a wireless communication prototype, based on a physical arterial blood pressure monitor which will be able to send data to a web server due to an integrated ESP8266 Wifi interconnection module.

This article presents the prototype design, technological integration and components implemented. While it is true that multiple monitoring systems have been developed, in this case there are highlighted some machine learning algorithms associated with monitoring of BP measurements. This proves a technological integration which involves data collection in the cloud, pervasive computing, embedded systems and data analysis. These algorithms are still a work in progress and will be published as a E-heartBP continuation.

Keywords— [Internet of Things (IoT)], [Blood Pressure], [Machine Learning], [Telemedicine].

I. Introduction

Recently, technological convergence in health care has become relevant because it is a promising alternative for the treatment of patients with chronic diseases. Some concepts based on Internet of Things (IoT), such as context sensitivity, ubiquitous computing or wireless sensor networks help to build a large range of health care institutions, protocols and models. Some monitoring models oriented to policy planning and others to self-care. These latest have posed technology challenges associated with continuous care in home, involving the participation of different actors like patients, their relatives and a third party.

Some of the efforts that have been made in health care include the framework for monitoring patients with chronic diseases, such as the model based on ontologies and the care network for patients with chronic diseases [1], or the "Aware Home Research Initiative" (AHRI) at Georgia Institute of Technology, focused on addressing the fundamental technical, designing and social challenges for caring people in home.

As indicated by the foregoing, the main purpose of this research is to design and to develop a prototype of wireless communication using an existent arterial blood pressure monitor, which will be able to send data on a web server. To achieve this, it is required to collect leading researches in the area; analyzing its weaknesses, strengths and relevance for the development of the prototype.

This prototype is part of a large work that involves a machine learning algorithm which is currently being developed. This algorithm aims to process blood pressure data measured by the device, which offers an alternative of analysis with better quality and precision features, fundamental in matters of people health and welfare. This development is consistent in the current technological context of IoT and its publication is planned in the short term, as a complement of E-heartBP.

This article is divided into Six sections. Section II presents the background related to Cardiovascular Diseases (CVD), classification of blood pressure (BP) values and disadvantages found in the current technics for taking BP measurements. Then, Section III deals with related works focus on CVD monitor systems supported by enabling IoT technologies. Subsequently, it is highlighted the most relevant machine learning methods that provide a prognosis of a CVD. At the end of the chapter, it is shown the relevant challenges in the referenced researches which will frame the data analysis stage.

One aspect of interest in this review is the transversally of IoT, as a repertoire of solutions for an intelligent BP monitoring system. In this order of ideas, Section IV presents the prototype methodology, where is highlighted the essential IoT layers and the work developed in each one: perception, application and network. Then, in section V it is exposed an analysis of the prototype contrasted with the consulted researches in terms of portability, data visualization and information treatment.

Finally, in section VI some conclusions are outlined, highlighting the proper data algorithms which can be applied to the prototype; this is a contextualization of the work in progress.

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II. CONTEXTUALIZATION AND CHALLENGES

Previous researches have demonstrated the timely use of IoT enabling technologies nowadays. These could improve not just the people quality of life, but helping in prevention or treatment in healthcare. Particularly, this section aims to show the importance of dealing with CVDs, a view of BP diagnosis in medical centers and those aspects of portability and accuracy to keep in mind at designing the prototype.

A. Incidence of cardiovascular diseases

According to the World Heart Federation [2], CVDs causes 17.5 million deaths each year and is the leading cause of death worldwide. Compared to cancer, the ratio is up to twenty to one, it means for a person who dies of any type of cancer, twenty of them die owe to cardiovascular diseases. Referring to Colombia, Figure 1 shows worrying statistics; nearly 30% of the total deaths in the territory correspond to CVDs. According to a report about the promotion of cardiovascular health [3].

In the last report, it is emphasized the relevance of researches which use the tools of the technologies ecosystem in healthcare. The ministry of Health and Social Protection of Colombia, indicates the importance that industries of health sector is constantly innovating with applications or information systems that identify previously the risk of any CVD, as well as improve the quality of the medical service comfort [3].

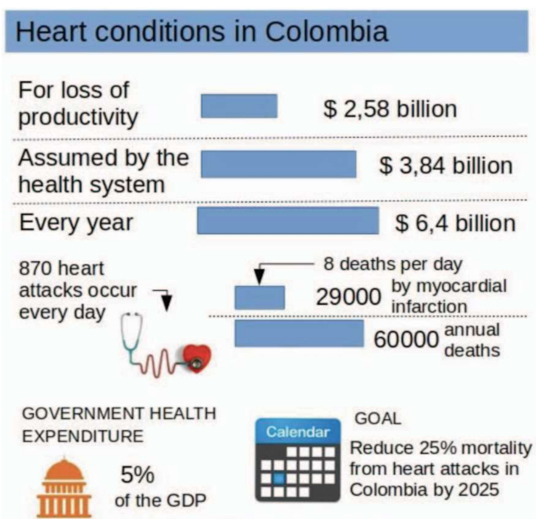

Fig. 1. Statement about cardiac conditions in Colombia. Source: [3]

B. Classification of blood pressure values

BP is defined as the force exerted by the blood towards the walls of the arteries. When the heart pumps blood, it is called systolic blood pressure (SBP), which has a value close to 120 mmHg. Then, when the heart remains at rest between beats, the diastolic blood pressure (DBP) is detected, whose ideal value corresponds to 80 mmHg. The reference values established for the level of BP are listed in Table I:

TABLE I. RANGE OF VALUES OF SYSTOLIC AND DIASTOLIC BLOOD PRESSURE

Degree of blood pressure	Blood pressure range
Normal	SBP >120 and DBP 80 mmHG
Pre-hypertension	SBP 120-139 or DBP 80-89 mmHG
Grade 1 hypertension	SBP 140-159 or DBP 90-99 mmHG
Grade 2 hypertension	SBP >= or DBP >= 100 mmHG

Source: [4]

According to the Table I, registers over 120 mmHG in SBP need to be monitoring in order to prevent future cardiac problems. This culminates in the terms of the "*Guide of attention of the arterial hypertension"* proposed by the Colombian Minister of Health [5]. The BP supervision protocol is supported in the following process: A request of a general medicine appointment asked by user; in the appointment, the regular doctor proceeds to check a vital signs and BP measurement. This process also mentioned by Arindam Ghosh [6], Hijazi, Page, Kantarci *and Soyata* [7] and Restrepo [4], specify some disadvantages which are:

• Absence of an automatic follow-up of the cardiac variables of the patient.
• Reliability of the diagnosis and dependency of the specialist.
• Impossibility of the medical service to react outside to any critical health event of the user.
• A short-term forecast makes impossible to identify related complexities.

The above descriptions show a work overview, which allows to prepare a device for measurement which capture and store data. However, this is not the novelty of this research. The innovative concept refers to the accessibility of the BP measures and the machine learning algorithms which process that data.

Ending with this section, it is relevant to expose the methods which are normally used by doctors at obtaining the BP values; the aspects reported in Table II must be taking into account when it is designed a system or prototype; accuracy shows the proximity level of the sensor measurement compare to the real value, whereas type of measurement indirectly shows how comfortable is the capture system.

TABLE II. METHODS FOR TAKING BLOOD PRESSURE

Method	Invasive	Continuous	Type of measurement	Accuracy
Palpation	No	No	Hint	Low
Auscultatory	No	No	Hint	Half
Oscillometric	No	No	Hint	Half-High
Penaz	No	Yes	Hint	Half-High
Tonometry	No	Yes	Hint	Half-High
Time Transit Pulse	No	Yes	Hint	Half-High
Intravascular Sensor	Yes	Yes	Direct	High
Extravascular Sensor	Yes	Yes	Direct	High

Source: [4]

A dataset of continuous BP measures could allow to find related cardiovascular information from the patient. These are relevant aspects that will be kept in in mind to develop an easy-use device that allows to record an historical set of measures that by processed, they will give significant information. The next section will address one of the goals of this research in build the said algorithms based on linear regression and artificial neural networks (ANN).

III. Background and Categories of CVD Monitoring Systems

The conclusion of multiple articles and researches show the relevance of the proper use of IoT devices, which are growing up in number into the environment. Consequently, the next paragraphs will emphasis in CVDs monitoring models and systems based on IoT, datasets and attributes available for algorithms training and techniques to manage and analyze those data.

A. CVD monitoring systems supported by IoT enabling technologies

A concept of great interest in the research of Unnikrishnan *et al.* [8] is tele-cardiology. This is related for caring and monitoring cardiac health from distance, it combines the intercommunication between data collection devices and the server that collects the cardiac measures. Particularly in this context, a research related to the cardiac diseases monitoring and long distance supervision [9] proposes a wireless monitoring model applicable to a specific complications in the area of cardiology. This research mentions factors that range from avoiding unnecessary re-hospitalization and more personalized health care, to effective communication between devices and platform data management.

These important aspects cited by the authors, make relevant the confidentiality of personal information in the cloud, interoperability of data between medical centers and data accessibility. However it is important to make relevant the attributes for early detection of an specific CVD; Hsu, Hsieh, Li and Yang [10] designed a heart rate data collection system based on the Metabolic Equivalent of Task (MET). The prototype sends data by means of an electronic handle to a mobile phone, then it is hosted on a cloud server. This process is carried out thanks to the MQTT message protocol available in the IoMT communication standards. In this way, users are provided with information or warning messages, as the case may be, about the physical efforts which involves the patient cardiac postoperative recovery process. One aspect to highlight of this project is the technological convergence in the user monitoring health status using Communication and Information Technologies CIT.

On the other hand, the evolution of devices that impose a technological avant-garde in the health field, in terms of portability and affordability, it is exposed in a case study carried out at the University of Rochester [7] which aims to deep into in the information generated by these devices use for medical use. Likewise, to distinguish non-relevant variables or information of minor importance. In this order of ideas, the implementation of machine learning algorithms can result in predictions that are reliable and with superior performance.

As it is mention in the next section, the attributes number, selected inputs and the quality of datasets, which make possible to perform mathematical equation or algorithm in which it would be possible obtain information derived from those raw data captured.

B. Attributes available in CVD datasets

According to the work of Acharya [11], Table III shows some of the datasets attributes available for the classification and prediction of CVD. This dataset was taken from the UCI machine learning repository. In the project, the author made a comparison between different machine learning classification algorithms, where is related the conditions that contribute to suffering a CVD. Results highlight the effectiveness of the Artificial Neural Networks (ANN), Bayesian Classifier (NB) and Support Vector Machine (SVM). Certainly, this deduction is going to be applied to structure the component of data processing which will be implemented for this prototype.

TABLE III. Database with Variables Associated with CVDs Used in Machine Learning Techniques

Attributes	Description
AGE	Age in years
SEX	Instance of gender (0 = female, 1 = male)
CP	Type of chest pain (1: angina typical, 2: angina atypic, 3: null angle pain, 4: asymptomatic)
TRESTBPS	Blood pressure rest in mmhg
CHOL	Cholesterol serum in mg / dl
FBS	Glicemy in fasting> 120 mg / dl (0 = false, 1 = true)
RESTECG	ECG results (0: normal, st-t wave abnormality, 2: lv hypertrophy)
THALACH	Maximum scope of heart rate
EXANG	Angina's induced exercise (0: no, 1: yes)
OLDPEAK	ST depression induced by the rest-exercise exercise
SLOPE	Picture of the peak exercise STS segment (1: pending up, 2: plane 3: pending down)
CA	Number of main glasses colored by fluoroscope (values 0 - 3)
THAL	Types of defects (3: normal, 6: fixed defect, 7: irreversible defect)
NUM	Heart disease diagnosis (0: healthy, 1: not healthy)

For the purposes of the present research, Table III. stores the next attributes that will be captured through de BP monitor:

- TRESTBPS, THALACH and DBP

Those refer to systolic blood pressure, Heart Rate (HR) and diastolic blood pressure respectively. Nevertheless, indirectly the data set is provided with the AGE, SEX, TIMESTAMP and the target variable (NUM). To deal with these data it going to be used the Tensorflow tool, owe to his practicality in build linear regression and ANN models, and to storing data it is used Firebase real-time database. This part of the prototype will be expose in detail in the methodology section.

C. Machine Learning techniques for the prediction of cardiac anomalies; ANN and SVM classifiers

With regard to the early detection of cardiac problems, Wang, Xia, Li, An and Chen [12], shows how ANN is used as the main technique, based on a logistic regression . The results of the study showed that processing static variables by ANN (exercise, weight, age, sex, among others) show a high precision index for diagnosing if the person can suffer a future episode of hypertension. According to the results, about 72% of assertiveness is associated with hidden neuronal layers. Similar results were found by Majed, Al-Mutairi, Sangaiah and Samuel [13], demonstrating how SVM, proposed for the design of a model fed with patients database with potential cardiac risk, afford results with a prediction accuracy of 87.9%.

However, in the computational context, there are equations to determine a certain level of risk of suffering any CVD. A study published by Unnikrishnan *et al.* [8] focuses on the level of sensitivity and specificity in the Framingham equation, alluding to the demographic variables of a given population. The predictive results of the study show the risk of contracting some CVD during the next 10 years. This type of particular improvements in the prediction algorithms make machine learning more efficient and sustainable as a medical tool.

As mentioned in this section, the possibilities of improving the efficiency in the prediction or prognosis of cardiac events increase considerably with the use of the learning techniques. Therefore, it is essential to know the parameters or attributes to be evaluated and to decide the classifier that suits, according to the disease and prototype.

D. *Technological convergence*

Azir [14] shows an issue related to data acquisition process in portable devices: the challenges that electrocardiography equipment face in measurement. In this article, interconnected devices based on IoT, significantly improve the aspects associated with portability, performance, data monitoring and affordability. One of the most relevant aspects of this study is the set of layers of communication architecture that must be handled by these medical devices (perception, network and application).

Continuing with a system which frames the mentioned layers, Ghosh [6] exposes a hypertension forecasting and monitoring system, in which an electronic handle (Wristband Empatica) and a processing platform (HEAL) are used. The research exposes the benefits of the cohesion between the practicality of obtaining data with electronic sensors and the intelligent processing of a cloud platform.

Keeping in mind these layers, the proposed prototype points out to the deliver a gadget which is settle in three general perspectives: An intuitive mobile interface developed in Android Studio. The modified blood pressure monitor which is able to send data through Wifi protocol owe to the ESP8266 module. The storage in Firebase that can be accessed by the user and selected people. And last but not least, the platform which analyses the captured data.

IV. Methods and System

The present research aims to applied ICTs to the design and implementation of a prototype supported by IoT [15]. It also highlights portability characteristics and intelligent processing of the collected data, where some information of the user can be forecasted and informed by means an application.

In this order of ideas, the design begins with the perception layer. It is used a wrist blood pressure monitor (Panasonic EW3106). This monitor is able to display heart rate, systolic and diastolic pressure data. As well has an EEPROM storage memory with I2C connectivity. The next paragraphs expose the challenges to face in building the prototype.

A. *Adhesion of characteristics*

Although the device or BP monitor is portable, it lacks some type of interconnectivity to transfer user data. Thus, the possibility of adding a wireless connection component is possible owe to the ESP8266 Wi-Fi interconnection module, as specified in [16].

The last modification requires accessing to the main board device and capture the data frame from the EEPROM memory which storages each of the user measures. It is possible when the device sends the data frame to the memory, and then through the ESP8266 pins, is possible to catch the information signal. Then this frame is understood due to the analysis of connection serial protocol. After a brief procedure, the module obtains the values of interest HR, SBP and DBP.

B. *App and database design*

With a monitor that can export data to a web server, communication standards and methods are specified in the network layer [9]. Whereas, the selection of a database which can storage easily the user's data, address to employ Firebase. Mainly for the use of JSON files which are light and easy to build for the hardware module (ESP8266). Also, it is granted an easy interaction with a mobile app which is the next step in the design. For the application layer is proposed an App whereby the user is able to see the features like his last BP record with the exact measurement time; a table with all the BP records Also a plot with all the registers for better visualization; and finally, an option which allows to prognostic a hypertension episode. Option in developing.

C. *Data processing*

Subsequently, an algorithm of Machine Learning, such as Artificial Neural Networks or linear regression, is planned to use for processing data stored in the database. This algorithm will produce timely alerts about possible and future critical events according to the analysis of the historical records. Figure 2, shows a general structure in IoT Which also is a frame for the presented prototype. Besides it is relevant to highlight the process made in all levels, that reflect a way to schematize the information flow and how is established the generation of notifications or relevant information to the user.

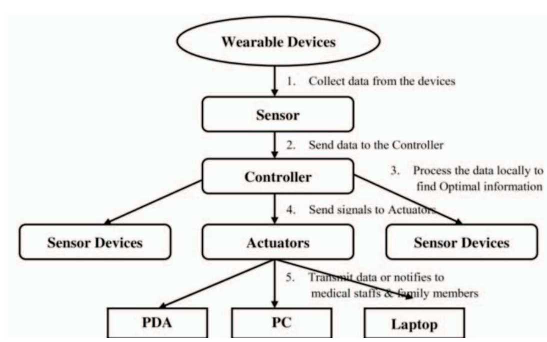

Fig. 2. Communication among things in healthcare Internet of Things [17].

V. Analysis of results

Due to the challenges exposed in section II, this proposal is intended to provide a solution in tele-monitoring, which will be comfortable to the user in terms of information visualization. The proposed prototype is consistent with the objective of the Ministry of Health of Colombia to reduce in 25% mortality from heart attacks in the territory by 2025, through the convergence of ICT applicable to the field of prevention and health care. Figure 3 illustrates the communication scheme.

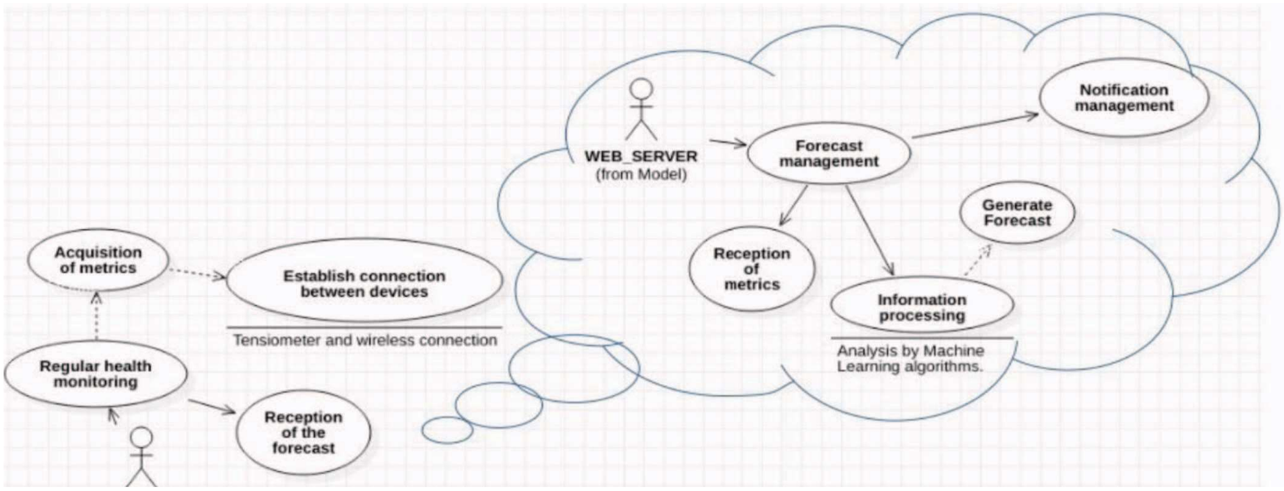

Fig. 3. Communication scheme of the BP monitoring prototype. Source: Authors.

In Colombia, arterial hypertension has been established as one of the leading causes of death. However, a model for the prevention of the disease using ICT has not been proposed [18]. In addition, it is worth to mention that the health sector industry is slowly innovating with applications or information systems that prevent cardiovascular risk [3].

The design of the prototype (Figure 3) proposes the use of a wrist blood pressure monitor, based on the oscillometric method for BP measurement, which achieves a medium-high accuracy (TABLE II). With this device, it is provided an acceptable reliability measurement index to the user. Additionally, an ESP8266 Wi-Fi interconnection module is added to export the data measured to a web server for later analysis. The last deals with the inability to interconnect the device.

In this article, the development of machine learning algorithms is based on the use of ANN and a dataset taken from Kaggle (an online community of data scientists and machine learners). The use of TensorFlow and Keras (libraries to develop machine learning models) is implemented through the use of the dataset from Kaggle and the data provided by the BP monitor, stored in firebase. After designing the model and training the one, Figure 4 illustrates the prediction percentage of the model, taking into account the target variable (Num) Table III, which refers to a possibility of acquire a cardiac complication.

The average model accuracy of the first model is 67%, however is important to mention that the model training was made with just 290 samples, which probably affects the results. Besides, it is relevant to mention that in this case, it is only used to make the prediction, 2 attributes of the dataset and it would cause down the model accuracy.

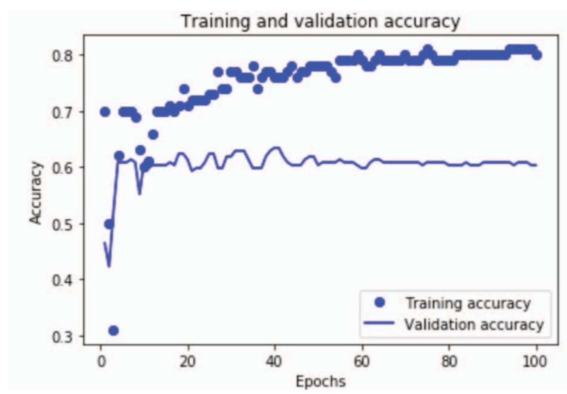

Fig. 4. Graph with the average values for accuracy model.

Contrasting this results with [13], the author achieved an accuracy of 72% in predictions. The value achieved with the prototype could be improved changing the number of samples in the training, the learning rate and the epochs. In fact, at the moment, it has been developing a testing model which involves additional layers for analysis and reduced number of iterations. It returns a prediction accuracy of 78%, nevertheless it is still in developing. The improvements will be published in a later version.

VI. Conclusions

The adhesion of the ESP8266 to the monitor, generates an additional consumption to the batteries, approximately of 10%. This is a point to improve, the energy consumption of the module exclusively in the events of capture and data sending.

The data storage from the monitor to Firebase and then the visualization by means of the app, it is currently taking from 10 to 40 seconds, with which the availability of the results is achieved almost immediately.

It is achieved an improvement on time of data visualization, where the medical staff and even the proper user are able to analyze the registration of multiples user measures, in a dynamic and comfortable way. Near to 3 minutes per medical checking are saved in each appointment compared to the traditional methods.

Related to the model's prediction accuracy, it has been obtained results to be improved, some of them could be parameterized through the model hyper-parameters, others by implementing a linear regression algorithm which will be able to predict the desired future values of the user dataset of measures. Achieving an average model accuracy of 78%.

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