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Towards Improving Hypertensive Patients Care: Pervasive Monitoring and Diagnosis Support

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Abstract

Hypertension is the most common chronic condition dealt with by primary care physicians and other health practitioners. It usually has no symptoms, causing a delay in diagnosis. Moreover, around 20% of the global population suffers from "white-coat syndrome", which can lead to misdiagnosing hypertension. When diagnosed, patients find it difficult to constantly monitor their blood pressure to ensure it is within acceptable levels. In this work, we propose a pervasive solution model for ambulatory monitoring of hypertensive patients and for supporting a clinician with the task of diagnosing hypertension. It contributes to the selection of attributes and techniques for assisting hypertension diagnosis, and also to an implementation which dynamically adjusts itself to each patient's average blood pressure.

Keywords:

Pervasive Healthcare; Assisted Diagnosis; Hypertension; Patient Monitoring.

Introduction

Arterial hypertension (HTN), has been globally recognized as the leading chronic disease that causes premature cardiovascular mortality and morbidity [1]. If HTN is properly controlled, cardiac mortality will decrease 49%, while cardiovascular mortality will decrease 62% [1]. Conversely, uncontrolled HTN, according to information from the Panamerican Health Organization (PAHO), could cause terrible health issues, such as myocardial infarction, kidney failure, blindness and/or heart failure [2]. Considering the above mentioned facts, an early diagnosis of the disease and providing mechanisms to maintain blood pressure within acceptable levels, is very important. However, there are issues that need to be addressed. First of all, at least 20% of the world's population suffers from "white coat syndrome" [4]. In the context of HTN, this means that a person's blood pressure readings might be higher in the doctor's office, but once he/she leaves the room, it goes back to normal. Another issue, which is opposite of the previous one, is "masked hypertension". It causes normal blood pressure readings in the doctor's office, but readings at home are in the hypertensive range [5].

Hypertensive patients, find it difficult to constantly monitor their blood pressure. In spite of the existence of well tolerated effective drugs, these are not enough to maintain blood pressure within acceptable levels [6]. It is claimed that around 20 million patients, will suffer a hypertensive crisis at some point of their lives [7].

This work presents a pervasive solution model to support hypertension diagnosis and provide monitoring of hypertensive patients. Supporting diagnosis by automated processing of data retrieved from patients could lead to more accurate diagnoses, while monitoring hypertensive patients could introduce several benefits. First, the patient is notified as his/her blood pressure starts to become abnormal. Second, every reading is stored in a central repository, allowing the clinician to view behavior of the blood pressure of any given patient and whether medication needs to be adjusted or not. Finally, the set of data in the repository, could be used in other research works.

This work is organized as follows. The next section presents recent work related to assisted diagnosis and patient monitoring systems. Then, a description of the proposed solution model is presented. Next, we present the methods used to perform tests and results obtained with them. Finally, a discussion of the results and a conclusion of this work is presented.

Recent Work

Assisted Diagnosis Systems

Most systems performing assisted diagnosis of hypertension use machine learning techniques, extracting features from available patient data or from available laboratory test results [8-11]. Whereas, others use techniques different from machine learning [12, 13], which we refer to as non-machine learning. Most of the works, in the non-machine learning group, ask for input from the user, by means of questionnaires or forms the patients need to fill in.

Currently, clinicians could make use of an ambulatory blood pressure monitoring (ABPM) device to diagnose hypertension when white-coat syndrome is suspected. It is worn by patients for 24 hours and once completed, it is connected to a computer that prepares a report for the patient [14]. A disadvantage of this approach is that it doesn't provide real-time notifications as blood pressure starts to become abnormally high, and that 24 hours might not be a long enough period of time to gather relevant data.

As a final point, we can mention that there are many challenges most work doing assisted diagnosis need to address, such as features to choose, sources of data to extract features from, and deciding whether to use machine learning or non-machine learning techniques, since better results might be obtained by choosing one or the other. This work tackles the challenges related to technique and attribute selection.

Patient Monitoring Systems

In this section, we focus on work performing patient monitoring by using wireless sensors and a smartphone to process data generated by them, that is, work oriented to pervasive monitoring. It is worth mentioning, that not only works monitoring hypertensive patients are considered.

There are studies that used specific sensors and machine learning to identify patient's health condition [15, 16]. Others allow use of any type of sensors, and apply machine learning techniques to check patient's health status [17-19, 34]. On the other hand, some apply non-machine learning techniques and do not constrain sensors to be used for monitoring [18, 20, 32, 33]. Works dedicated exclusively to monitoring hypertensive patients, apply non-machine learning techniques and some of them combine wearable sensors with sensors installed around the patient's environment [21-24].

Similarly to assisted diagnosis systems, these systems also face some challenges, such as developing a system that can adjust itself to every monitored patient, and one that can provide pervasive monitoring, that is, monitoring without disrupting patients' everyday activities. Other challenges are related to technological issues, medical issues, administrative issues, usability, and validation issues [25, 26]. This work tackles the challenge of providing monitoring by means of an implementation which dynamically adjusts itself to every patient that needs to be monitored.

Solution Model

In Figure 1, a graphical description of the solution model is presented. The model has the following behavior. Sensors transmit data over the air to the patient's smartphone. Once the device gets incoming data, it starts real-time processing to determine whether the patient's current health status is normal or requires attention. If it requires attention, an immediate notification is sent to the patient and clinician in charge. In order to support diagnosis, every piece of data is stored in a main server, where offline processing will take place once a diagnosis is required.

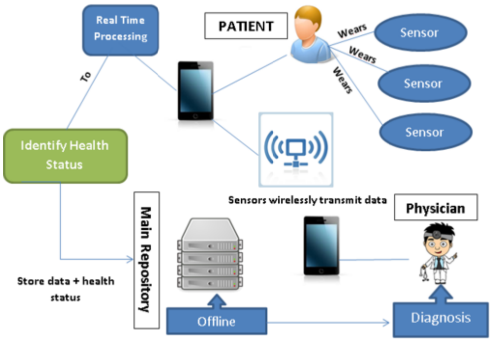

Figure 1 - Graphical description of the solution model

By monitoring a hypertensive patient, we expect to identify situations where severe blood pressure elevations occur. This is done by reading data from an ambulatory blood pressure device, which is attached to patient's left arm. This device measures blood pressure automatically, that is, without explicit request from the user. A smartphone will be in charge of processing the incoming data. Once an abnormal situation is detected, the patient, the clinician treating him or both will receive a notification. The model allows its components to be extended to easily include new sensors; for example, we could add an ECG sensor and include new notifications when emergencies occur.

For assisting hypertension diagnosis, we use machine learning techniques. Although we mentioned many works doing assisted diagnosis in the Recent Work section, there is not a golden rule that establishes which features will lead to reliable diagnosis support. Therefore, this solution proposes use of an activity tracking device, which a patient wears on his wrist, to include sedentary behavior as a new feature, since it has been proven that it is associated with a higher risk of hypertension [27]. Other features are weight, height, BMI, average systolic blood pressure (SBP), and average diastolic blood pressure (DBP).

It is worth mentioning that this is not an attempt to replace the clinician in the task of diagnosing hypertension, nor is it about ruling out standard diagnostic procedures. However, an obvious advantage of this solution model is that it considers longer periods of time, thus leading to more accurate and detailed information [30] which could improve diagnosis. Additionally, it also allows real-time notifications to patients and physicians as readings start to become abnormal. This would allow them to take actions earlier in emergency situations, whereas ABPM would only report abnormal values to the physician once he/she downloads the readings from the device.

Average blood pressure is also used for monitoring, since in order to identify a patient's health condition, the system uses values adjusted to this patient. This is a valid interesting approach since essential hypertension produces structural and functional modifications as a result of the growth or remodelling of blood vessels [28]. We will refer to these values as dynamic values. Previous work has used both dynamic and fixed values to monitor a hypertensive patient [22].

It is important to mention that for calculating average SBP and DBP, we used a weighted average equation (1) that proved to be better than arithmetic mean [24] when certain readings might be deleted due to errors. It considers the number of minutes elapsed between one reading and the next.

$$wAvg = \frac{\Sigma_i (L_i * P_i)}{\Sigma_i P_i} \tag{1}$$

$$P_i = \mid T_{i+1} - T_i \mid$$

Methods

Test Method for Assited Diagnosis

A prototype of the proposed model was built to perform tests. Even though blood pressure readings can be obtained directly from worn sensors, it is not mandatory to do so. It can also be obtained manually, by requesting a patient to measure his blood pressure and then providing an interface where he can upload the current reading. But this manual approach is less convenient, as the patient can inadvertently make mistakes and has to interrupt his activities to measure his blood pressure. But, this latter approach is convenient when wireless devices are not available, and has been adopted by this work for getting required data. Sixty patients were selected from two Paraguayan hospitals to be part of the tests. Only those 18 – 90 years old, who were able to measure their blood pressure, were enrolled. Patients were requested to write their blood pressure readings down every eight hours, until they completed 10 readings each. Sedentary behavior information, like blood pressure readings, can also be obtained manually by asking patient for information about physical activities performed every day. Once patients accepted to be part of the test, they were interviewed to find out about sedentarism and obtain demographic data. A doctor classified each one of the 60 patients as hypertensive or non-hypertensive (i.e. healthy).

In order to apply a machine learning technique for assisted diagnosis, the full data set was grouped in two sets. The first one contained 35 records and it was used as the "training set", while the latter had 25 records and was used as "test set". Records in the "training set" were partitioned as follows: 20%

of the patients were sendentary and hypertensive, while 8% were hypertensive but non-sedentary. Additionally, 43% of them were non-sedentary and healthy, while 29% were sedentary and healthy. The test set was divided as follows, 40% of patients suffered from hypertension and 60% were healthy. We used an online learning algorithm consisting of a variation of gradient descent, since most work dedicated to assisting diagnoses choose online learning algorithms to generate suggestions [31].

In order to validate the assisted diagnosis systems, a confusion matrix was built. A confusion matrix is a table of at least size m by m, where an entry, CM(i, j) indicates the number of cases i labelled by the system as class j [29]. For the system to have good accuracy, values along the diagonal would be far from zero, while the rest would be close to zero.

The following measures were taken into account [29]:

1. Sensitivity: refers to how well the system can identify a hypertensive patient (True Positive / Positive).
2. Specificity: refers to how well the system can identify a healthy patient (True Negative / Negative).
3. Precision: used to access percentage of hypertensive patients that are actually hypertensive (True Positive / (True Positive + False Positive)).
4. Accuracy: It is a function of sensitivity and specificity (Sensitivity * Positive / (positive + negative) + Specificity * Negative / (positive + negative)).

Where:

- Positive is number of hypertensive patients.
- Negative is number of healthy patients.
- True Positive is number of patients suggested as hypertensive that actually are hypertensive.
- True Negative is number of patients suggested as healthy that actually are healthy.
- False Positive is number of healthy patients suggested as hypertensive patients.
- False Negative is number of patients suggested as healthy but actually suffer from hypertension

Test Method for Monitoring System

The monitoring system is comprised of two main components, a data gathering component and a health condition inference component. For testing purposes, simulated blood pressure readings were used, that is, the data gathering component did not connect to sensors, instead it obtained data from a simulator. The simulator starts with a patient's average SBP and DBP values, and then several events are generated, where each event would alter a patient's blood pressure. An event could be one of the following: **salty food, rough emotions (e.g., anger), physical activity, relaxation, and no change**. Each event, but the last one, causes blood pressure to increase or decrease by three levels: low, medium, high. The health condition inference component calculated average SBP and DBP as new events appeared, using the weighted average formula described in the Solution Model section. However, since values were simulated and none of them was invalid, weighted average and arithmetic median would have lead to the same values.

To perform tests, three fictitious hypertensive patients were created and events were generated all day long every 30 minutes. That is, 48 readings per day with a total of 240 readings for each patient, since these fictitious patients were monitored for five days. Even though blood pressure readings were simulated, we expect to test the system with real patients and sensors in upcoming phases.

The purpose of the test was to observe the differences between using values adjusted to each patient (i.e. dynamic values) and fixed values.

Results

Test Results for Assisted Diagnosis System

In Table 1 we can observe the results obtained after performing the test. The system indicates that 10 patients suffer from hypertension and 12 patients are healthy. It has a false positive rate of three, which means that three patients are considered hypertensive even though they are healthy. It does not generate any false negatives. It has 100% sensitivity and 80% specificity, which has been affected by the existence of false positives. This also affected the obtained precision, which was 77%. Finally, the system has 88% accuracy, which is affected by the specificity the system has.

Table 1 - Values obtained for each measure

Measure	Value
True Positive	10
True Negative	12
False Positive	3
False Negative	0
Sensitivity (%)	100
Specificity (%)	80
Precision (%)	77
Accuracy (%)	88

Test Results for Monitoring System

In Figure 2, we can observe SBP and DBP values for patient P1 during a single day, displaying generated alerts. Dashed orange and solid red lines represent warning and critical alerts for dynamic values, respectively. Whereas, dotted light blue and mixed blue lines represent warning and critical alerts for fixed values, respectively.

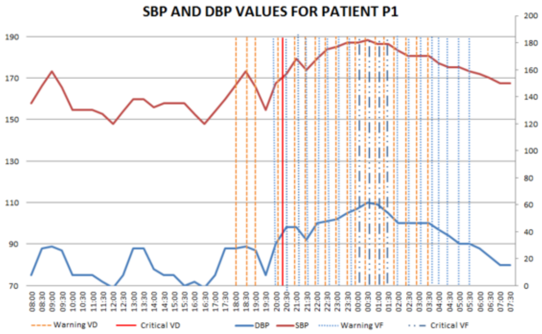

Figure 2 - SBP and DBP values for patient P1 for a day. Warning and Critical alerts are shown for both dynamic values and fixed values.

It is important to note that only one critical alert was generated when dynamic values were used. Though SBP/DBP values higher than the one at the specified time were generated, only warning alerts occurred later. This is due to the average blood pressure of P1 adjusting itself to a new value. However, this might be seen as an incorrect behavior because in practice, average blood pressure cannot change in such a short period of time. Thus, Figure 2 exposes two important matters to be defined when using dynamic values instead of fixed ones, that is, the time window to consider blood pressure readings for calculating average blood pressure and the frequency at which blood pressure is to be measured. These must be defined so that average blood pressure is realistic.

The results from the tests are displayed in Table 2. We can observe a lower number of warning and critical alarms when dynamic values are used.

Table 2– Results for Monitoring System

Patient	Fixed Values		Dynamic Values	
	Warning Alarms	*Critical Alarms*	*Warning Alarms*	*Critical Alarms*
P1	80	20	76	3
P2	103	92	57	4
P3	120	71	86	5

Discussion

In Table 3, we show the results obtained by work dedicated to assisting hypertension diagnosis along with ours. Information in the table encourages us to believe that we are on the right track since sensitivity and specifity values are greater than those obtained by some recent works. However, a comparison cannot be made since datasets are different. Our results might be improved, perhaps by using larger datasets or by trying different attribute combinations.

Table 3 - Values obtained by others and this proposal

Measure	Su&Wu	Ture et al.	Hsu et al.	Proposal
Sensitivity	46.89%	95.24%	--	100%
Specificity	73.96%	71.79%	--	80%
Accuracy	72%	--	92.8%	88%

The monitoring system obtained results similar to those in [21], where the authors showed that fewer alerts are generated when values adjusted to patients are used. We expect that, in practice, this translates to generating critical alerts only when a patient's current health status needs attention from the clinician in charge.

Conclusion

This work presented a pervasive solution model to support hypertension diagnosis and provide monitoring of hypertensive patients. Although, there are many works on assisting diagnosis, there are challenges that need to be addressed. One of these is the selection of features to be used to accomplish the task. This work introduced a feature that previously mentioned works had not included, that is, whether a patient has sedentary behavior or not. We also contributed to the selection of a diagnosis technique, by choosing an online learning algorithm different from artificial neural networks and support vector machines, which are the most commonly adopted techniques by recent works.

Furthemore, identifying a patient's health condition, by using values adjusted to himself, allowed the system to generate fewer alarms than the case when fixed values were used. In the context of hypertension, this is a valid approach, since a severe blood pressure elevation might represent a crisis for some patients, but it might not be dangerous for someone who often has high blood pressure.

As future work, we expect to try the prototype with real patients. That is, to obtain data from the ambulatory blood pressure sensor and process them in real time instead of simulating readings, since this will allow us to create a confusion matrix; and perform an analysis similar to that in Test Results for Diagnosis System. We also expect to get feedback from doctors and patients to validate the system.

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