A Remote Medical Monitoring System Based on Data Mining

Roumaissa Bekiri, Abdelhamid Djeffal and Messaoud Hettiri

May 10, 2020

A Remote Medical Monitoring System Based on Data Mining

Roumaissa Bekiri
Computer science department
Mohamed Khider University of Biskra
bekiriromaissa@gmail.com

Abdelhamid Djeffal
LESIA Laboratory
Mohamed Khider University of Biskra
a.djeffal@univ-biskra.dz

Messaoud Hettiri
Electrical engineering department
El Oued University
hettiri-Messaoud@univ-eloued.dz

***Abstract*—The field of e-health is experiencing rapid and growing progress with the evolution of the means of communication and health data acquisition through smart watches such as heart rate, temperature, glucose level. , ... etc.**

This work proposes a system of automatic remote monitoring of the health of individuals based on smart watches worn by patients and doctors as well as a centralized server of the administration. The former uses accumulated patient data to build decision models using machine learning methods. These models are used to automatically track the health of patients. The system has been designed, implemented and validated on data concerning cardiovascular diseases.

***Index Terms*—Medical Surveillance, Physiological Measurement, Data Mining, Machine Learning, Smart Watches, SVM (Classification).**

I. Introduction

According to recently published statistical reports from the United Nations, the average age of the population is expected to grow rapidly in developed countries in the next decade, leading to a very significant increase in the cost of health care. However, the latest technological innovations in the different fields are timely for the implementation of new, more effective and affordable approaches to the management of people's health.

Health care is an essential part of human life. Each of us needs periodic monitoring of vital parameters and appropriate treatments based on our medical data and health status.

Remote medical surveillance services are experiencing a growing demand, generally coming from chronically ill patients [7] and particularly elderly people due to their frequent travel constraints [5].

People to be remotely monitored can be elderly people, people with reduced mobility, sick people with chronic diseases or anyone who wants to monitor their health. These services rely on new technologies to monitor patients' activities without requiring patients to visit medical or testing centers.

These processes become important when people become old and with chronic diseases such as cardiovascular disease, diabetes, non-equilibrium heart rate, Parkinson's, cancer ... etc, and are not able to track their condition properly without a specialized medical personnel or sophisticated equipment for surveillance especially in remote cities. In emergency situations, the patient must be transported to the hospital, observed by medical personnel and treated in time if certain parameters are abnormal. In many cases, even a short delay could lead to dangerous consequences including the death of the patient.

Nowadays, different patient monitoring systems have been proposed and implemented for different purposes such as: obtaining patient health information quickly and efficiently, saving material and financial resources due to patient travel to different medical centers, periodic monitoring and alerting in case of emergencies better for the elderly or disabled, are able to provide reliable information and continuously on the patient.

The development of technologies, especially in the field of digital health, enables rapid control of individuals through means such as smart watches, telephones, tablets, etc. In our work, we are interested to connected watches (Smart watch health)[**?**].

Our proposal consists of the combination of the latest developments in the smart watch market and devices for the detection and capture of physiological signals of patients with machine learning techniques. The goal is the design and implementation of a continuous and efficient monitoring system based on analysis using data mining methods.

Our approach is based on collecting the health data of people and storing them in a centralized information system to analyze and monitor the health status of these people in a real time and continuous way.

The proposed system uses smart watches worn by patients and physicians and connected through communication networks to a remote management server. This server uses collected data from watches such as heart rate, temperature, movements, glucose level, ... etc. to learn decision models for early detection of diseases in people.

This paper is structured as follows: Section 2 presents some existing proposals for remote health monitoring. The section details our proposal and its various components. Section 4 presents the impementation of our proposal as well as some results obtained. Section 5 concludes the paper and presents some perspectives.

II. Related works

In the literature, several solutions have been proposed to facilitate the task of remote medical monitoring of patients through devices connected in real time and periodically:

A. Mobile Patient Monitoring System (MPMS)

Authors of [10] propose a mobile digital patient monitoring system PC-based and PDA-based. This system gathers the physiological data of the patients by the sensors and biosensors. The data is routed to the PC or the phone/PDA cell of a patient. After an analysis of critical situations and possible alert determination, these devices transmit this data to the server for the complete analysis.

After the data is analyzed, the medical server provides the results to the PCs or to the patient's phone / PDA cells. Patients can take necessary action based on these findings. Structurally, the proposed SMSP consists of three essential components (Figure 1):

- Wireless LAN.
- Local home-based service (LHS) accessible by the patient, his assistant or a family member.
- Remote medical server (RMS) accessible by the doctor or any other authorized person.

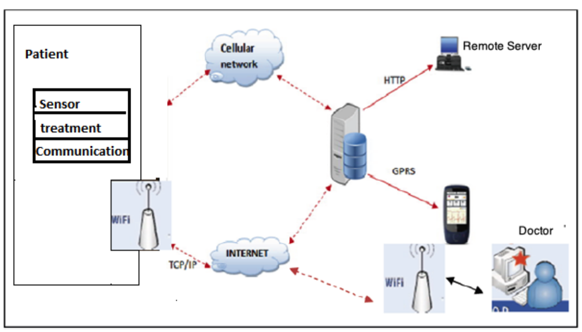

Fig. 1. Mobile Patient Monitoring System (MPMS).

B. System using sensors

The authors of [2] propose an architecture allowing to quantify the heart and respiratory rhythms according to certain conditions of movement. The elements used are: computers (PC), webcam, PPG sensors on the finger. Their operation is inside and relative to the sources of lighting. A sensor is placed on a patient's finger and simultaneously measures the heart rate and amplitudes of the PPG signal. All this data is saved at the PC level. The following figure describes the proposed architecture:

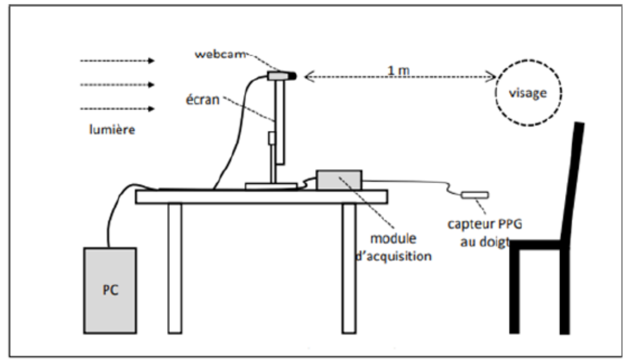

Fig. 2. System using sensors[2]

C. Smart watches

Connected watches are smart watches that have multiple functions. Indeed, these tools are the results of the introduction of new technologies in the watch sector. With these tools of last generation, it is not only a question of putting the watch to learn about the time. Connected watches or Smart Watches are mostly equipped with Bluetooth, WiFi and GPS to provide real data to their users when they are activated [1]. The evolution of these smart watches has also touched the field of health by proposing the taking of several measures such as the heart rate, the blood pressure, the temperature of the human body, the speed of movement, the rise of the clutches and the distances and lastly the cardiac signal (ECG). These measures make it possible to monitor in real time the health status of users, particularly those with certain diseases such as cardiovascular diseases, diabetes, Parkinson's disease, etc. Currently, there are several smart watches that offer different health measures, among these measures we quote:

1) Heartbeat: Most smart watches are interested in following cardiovascular disease through the number of heartbeats, whether low or high, they are sometimes a sign of a serious illness. But these symptoms often go unnoticed, which makes it impossible to diagnose the causes. Smart Watches automatically alert the user to medical conditions as needed so that they can take immediate action and consult a doctor.

The digital clip-on heart rate sensor shown in Figure 2 (b) is a high-performance optical sensor that measures the change in blood movement in the body [3].

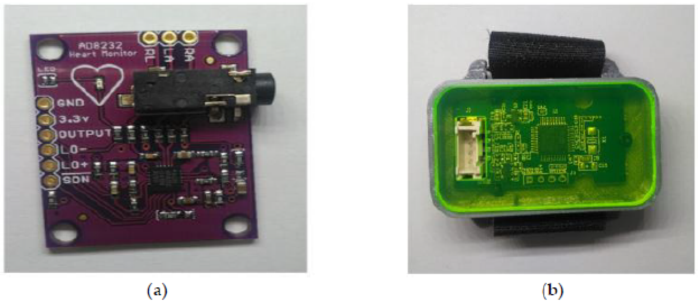

Fig. 3. Optical biosensors: a) Electrocardiogram (ECG) cardiac monitoring sensor (b) Fingerprint heart rate sensor

2) Heart signal: The electrocardiogram (ECG) is a signal that represents the electrical activity of the heart. The ECG is essential in the surveillance of patients or in the diagnosis of cardiovascular disease. The following figure shows an electrocardiogram (ECG) signal:

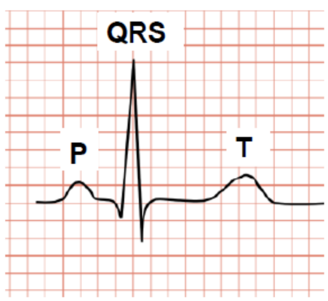

Fig. 4. Electrocardiogram signal (ECG) [8]

A recent smart watch can accurately display the heart's electrical activity through specific sensors and notify people with relative illnesses.

3) Blood pressure: The smartwatch combines EKG (electrocardiogram) and PPG (photoplethysmography) sensors to measure the user's blood pressure in real time

Fig. 5. Smart health watch for measuring blood pressure

4) Glucose level: Through specific glucose sensors, smart watches can monitor blood glucose levels and track diabetes status in a patient at any time. It is important that blood glucose stays within a healthy range. If the blood glucose gets too high and stays high, it can cause damage or complications to the human body [9].

Fig. 6. Smart watch (K'Watch) to measure glucose levels [6]

5) Temperature: Connected watches also take, via sensors, the value of body temperature.

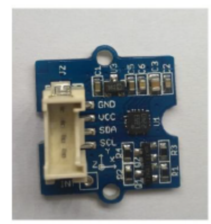

Fig. 7. Capteur de température du corps humain [3].

III. Proposed system

The proposed system aims to monitor the health status of individuals at any time through connected Smart Watches, to take sanitary measures, to collect the corresponding data in a database to which processing and diagnostic algorithms and possibly generate alarms or initiate interventions.

General architecture of the system

The following figure 8 represents the overall architecture of the proposed system composed of three main parts: patient part, doctor part and administration part.

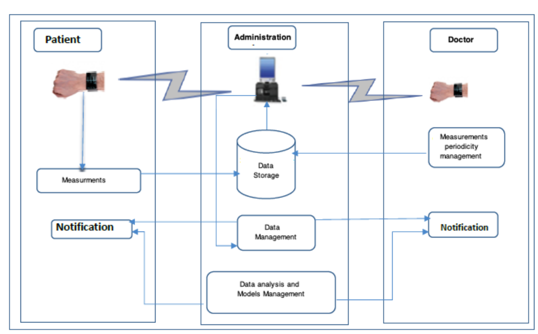

Fig. 8. Proposed Remote Medical Monitoring System (RMMS) Architecture.

A. Patient part

At the patient level, the smart watch collects possible medical measures and sends them regularly or at the request of the administration party to the system that stores them and uses them for decision making. The watch also receives notifications from the administration part of data mining models or doctors.

B. *Administration part*

The administration level information system collects all information about patients and their health measures as well as information about doctors and their decisions in the form of a database.

The information system administrator oversees its operation. It validates the registered physicians after their profile verification, builds and validates and activates the decision models and controls the system parameters such as the application periods of the decision models. It mainly performs two important tasks:

1) Model creation: The creation of a decision model can be done from two sources:

- *External database:*
  In the case where an internal base is not yet ready during the first times of use of the system, the administrator acquires a training base from a hospital, a medical center, a research center, .. etc.
- *Internal Database:*
  After running the system for a sufficient period of time, he can collect a training base. In this case a pre-processing phase on the data collected in the measurement tables is necessary.
  In both cases, the administrator uses an automatic learning method such as SVM (Machine Vector Support) to build a decision model from the database used

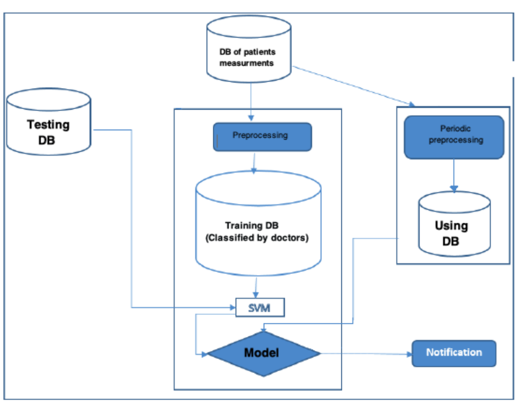

Fig. 9. Construction and use of models at the administration level.

2) Application of the model:

C. *Physician part*

On the doctor-side application, the latter indicates to the system administrator for a patient that he follows the measures to be checked and their periodicity. After applying a decision model on patient data, the administrator informs physicians of the results obtained to inform them about the status of their patients and also to check the effectiveness of the model and improve its performance.

IV. Experiments and Results

The proposed system was simulated using a network and web applications each representing a part of the system. In the administration part, we built decision models from an external source and validated them with cross-validation.

A. *Tools and data used*

To validate our proposal, we used several tools for coding, conversion, communication, and administration.

To validate the decision models, we used the public database "Heart deaseas" [13] available for free access on the UCI data mining site and a collection of medical diagnostic reports of 270 patients aged at least 29 years, of which 120 cases are in chronic disease and 150 cases healthy. The first 13 attributes of the base represent risk factors for the disease while the 14th represents the class of the patient (Absence (1) or presence (2) of heart disease).

The following table shows the data characteristics:

Attributs	type	Min/Max	Moyenne
age	real	29/77	54.43
gender	binary		
type of chest pain	nominal	(4 valeurs)	
resting blood pressure	réel	94/200	131.344
serum cholesterol in mg / dl	réel	126/564	249.659
Fasting blood glucose> 120 mg / dl	binary		
electrocardiographic results at rest	nominal	(0,1,2)	
maximum heart rate reached	real	71/202	149.678
exercise-induced angina pectoris	binary		
oldpeak = ST depression induced by exercise compared to rest	real	0/6.2	1.05
the ST segment slope of the exercise peak	Ordered		
number of main vessels (0-3) stained by fluorescence	real	0/3	0.67
thal	nominal	{normal,fixed reversible }	

Fig. 10. Characteristic of the database used

B. *Mesures*

o measure the performance of built models, we used precision and recall. Precision (or positive predictive value) is the proportion of the relevant items among the set of items proposed, so accuracy can be understood as a measure of accuracy or quality, precision is calculated using the following formula. DataMining [11]:

$$\text{Precision}_i = \frac{\text{Nb of examples classified in class } i}{\text{Nb of examples in class } i}$$

recall (or sensitivity) is the proportion of the relevant items [4] :

$$\text{Recall } i = \frac{\text{Nb of examples correctly classified in class } i}{\text{Nb of examples in class } i}$$

Recall (or sensitivity) is the proportion of the relevant items

C. Results

We conducted several tests to make a tunning and choose the right parameters to give the best results in terms of recognition and recall rates.

The parameters used for tunning are as follows:

- Test data: The model is tested on training data and on external test data.
- Used Kernel :RBF and polynomial.
- the gamma parameter for the RBF kernel.
- Parameters of (polynomial degrees) for the linear kernel [14], [12].

The following figure 11 represents the evolution of precision and Recall depending on the degree: by testing on the training data and using the Polynomial kernel of the SMO method:

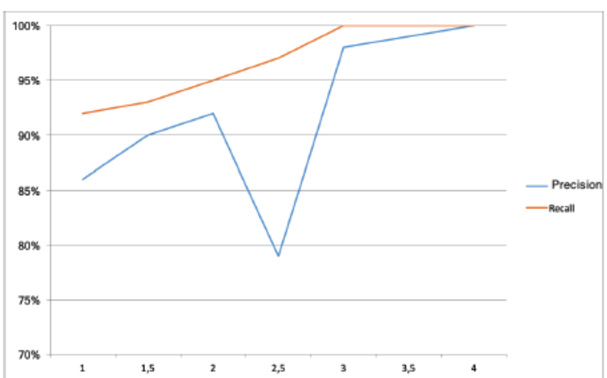

Fig. 11. Precision and Recall according to the degree of the polynomial kernel for the SMO method

The following figure ref Fig11 represents the evolution of accuracy and Recall as a function of degree by testing the training data and using the Polynomial kernel of the LibSVM method:

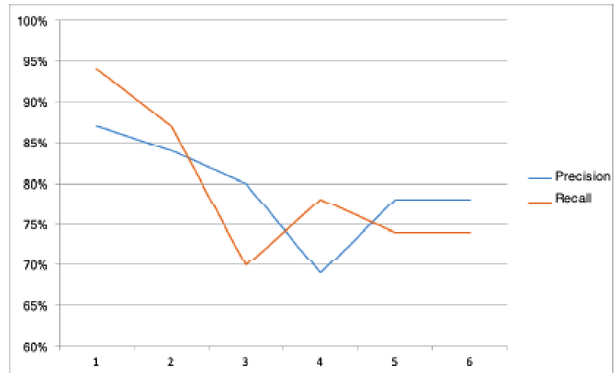

Fig. 12. Precision and Recall according to the degree of the polynomial kernel for the LibSVM meth

D. Discussion

From the previous figures, it turns out that the best results that can be obtained in terms of precision and recall are those using the RBF core with a gamma = 0.08 and the LibSVM method. The accuracy is then 90% and the recall is 99% because of the good compromise it has between accuracy and Recall. Through all our experiments and results, we can say that our proposed system is able to correctly identify 99% of the cases of patients affected by cardiovascular diseases.

V. Conclusion

With the advent of new technologies in the digital health field, and the growth of the human population, medical surveillance systems have become of paramount importance. We have studied in these work these systems and proposed a solution based on smart watches.

We designed and built a remote medical surveillance system that combines three main parts: patient, doctor and administrator.

Patient and physician applications are located on smart watches and are responsible for collecting patient data and reporting to physicians

The administrator application is located on a remote server and is responsible for building and using automated decision models for early detection of diseases. We finally validated our proposal with an application on the case of monitoring cardiovascular diseases.

The recognition rate obtained on the training data exceeds 97%, which is very encouraging and demonstrates the effectiveness of the method proposed.

For future work, we suggest some ideas that can improve our system such as:

- Improved applications on watches for better system settings.
- The application of the system in real cases to build training bases.
- Strengthen the administration system with other machine learning methods to improve its accuracy.

References

[1] Apple Watch Series 4. https://www.apple.com/ca/fr/apple-watch-series-4/health/, Septembre 26, 2018.

[2] Frédéric Bousefsaf. *Mesure sans contact de l'activité cardiaque par analyse du flux vidéo issu d'une caméra numérique : extraction de paramètres physiologiques et application à l'estimation du stress*. PhD thesis, Université de Lorraine, Novembre 2014.

[3] Saraju P. Mohanty By Prabha Sundaravadivel, Elias Kougianos and Madhavi K. Ganapathiraju. Everything you wanted to know about smart health care,evaluating the different technologies and components of the internet of things for better health. *IEEE Consumer Electronics Magazine*, january 2018.

[4] AbdelHamid Djeffal. *Fouille de données Avancé*. Université Mohamed Khider, Biskra 2018/2019.

[5] Rahman Jamal and Herbert Pichlik. *LabVIEW applications and solutions*. Prentice Hall PTR, 1999.

[6] Braden Siempelkamp Josh Piemontesi and Gordon Minaker. Smartwatches & biometrics for personal health monitoring. *SLIDO*, 2009.

[7] Frank Alexander Kraemer. Engineering android applications based on uml activities. In *International Conference on Model Driven Engineering Languages and Systems*, pages 183–197. Springer, 2011.

[8] Mokhinabonu Mardonova and Yosoon Choi. Review of wearable device technology and its applications to the mining industry. *Energy Review*, March 2018.

[9] Montre K'Watch Glucose et mesure du glucose en continu. https://diabete-infos.fr/kwatch-glucose-montre-mgc/, December 19, 2018.

[10] Diaf Radja. *Système Embarqué Communicant pour la Surveillance Médicale des Personnes à Domicile*. PhD thesis, 2014.

[11] Drid Abou Bakr Seddik. *Pattern Recognition for health care analytics*. PhD thesis, 2017.

[12] Swasti Signal and George D. Monika Jena. Astudy on weka tool for data preprocessing classification and clustering. *International Journal of Innovative technology and exploring engineering (IJItee)*, 2((6)), 2013.

[13] Statlog (Heart) Data Set . https://archive.ics.uci.edu/ml/datasets/statlog+(heart), July 15, 2018.

[14] Lechevallier Y. *WEKA, un logiciel libre d'apprentissage et de data mining"*. INRIA-Rocquencourt.