Capítulo 1 Sistemas de monitoreo en tiempo real para la atención médica a través de árboles de decisión

Chapter 1 Real-time monitoring systems for medical care through Decision Trees (DT)

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Abstract

The application of information and communication technologies (ICTs) has had a considerable impact on the development and search for knowledge. An objective in the field of medicine complemented by ICT is to improve patient care and communication of vital signs through the use of emerging technologies. For provide clinical care to elderly people it is vital to determine the presence of falls to alert staff or family members to provide first aid and avoid the development of more severe conditions or psychological problems. This paper explains the development of an embedded system that is responsible for monitoring the state of elderly patients through a bisensory system (temperature and user movement) that verifies the location of temperature and the difference in the X, Y and Z axes to determine the states of emergency in order to know any possible fall or problem in the patient's environment. The communication between the user of the device is done through a platform specialized in Internet of Things (IO), the information received is processed by adding a Decision Tree to know with certainty when a patient is at risk. The Decision Tree presented has an accuracy of X% in an evaluation of the ROC curves, therefore, can be applied to patients who are in a geriatric.

Decision Tree, Artificial Intelligence, Microcontroller, Statistics, Multiclass, Medicine, IoT

Introduction

Let us imagine that we are in a health care center, which has several areas, each of them treated differently through specialists, one of them and that has gained prominence in recent years is the geriatric area. Recently, several devices have been implemented to detect or help the attention of this population, in search of providing quality care to each of the individuals.

However, geriatric hospitals present different complications, from the meticulous physical care of each patient to their psychological vigilance, thus alleviating the workload of the workers.(Tinetti & Williams, 1997) The objective of the proposed device is helping the elderly patients who are faced with some of the most common discomforts, such as increased or decreased temperature in the environment where they are, same factors that must be treated immediately from the medical point of view, or have a fall, which at a certain age represents a risk of bone injury. With this it is possible have an overview of what happens to all patients in real time, since the current device has Internet modules Things (IoT) including Artificial Intelligence techniques provides a mathematical point of view well supported by years of experience and work, therefore, it could be concluded that such a device can be used in initial tests in order to improve the tools that has been integrated in this research.

Background

Falls are defined as events where the individual loses balance, generating a loss of force in its center of gravity causing the individual's body to knock against the floor or surrounding structure generating from injuries to loss of consciousness. (Hazzard, 1994)(Ungar et al., 2013) Specifically, in case of presenting falls in older adults this generates a latent risk, which results in physical sequels such as contusions, broken hips (Tsuda, 2017), injuries that inhibit the mobility of the individual temporarily or permanently, and in certain cases psychological problems such as depression, sensation of repeating the fall and in the worst case, the need for psychological help in order to remove the trauma (Evans et al., 2015).

As a result, numerous techniques have been developed in the medical area to provide health care in this situation. There are many techniques for care are based on medical knowledge, which is, the geriatric specialists analyzes the state of their patient and they provide physiological treatment, in other words, help the patient to ease the physical pain perceived because of the falling (Zhao et al., 2017).

The use of rehabilitation techniques is used to repair the tissues and muscles damaged by the fall and even medicines are used in order to reduce the pain (Luk et al., 2015). Although this area of medicine is improving every day, the application of technologies in everyday life has begun to extend into different fields of science, including the field of medicine and telemedicine (Armstrong et al., 2017)(Sebestyen et al., 2014).

From this viewpoint, a new concept has appeared today denominated electronic health, or e-Health. An e-Health objective is the ability to monitor the patient's clinical situation, enhancing the existing relationship between the medical staff and the patient, positioning the patient as an active role of the healthcare, providing to the medical personnel of indicators of their physical condition during the daily routine (Farahani et al., 2018)(Savola et al., 2012). This aspect is very important in monitoring vital signs of the elderly people, for example the cases presented by De Venuto et al. (2016) describes the use of a wearable system which integrates a wearable electroencephalography (EEG) and electromyography (EMG) in order to detect potential falling (De Venuto et al., 2015).

During monitoring of vital signs in elderly people it is essential to determine the position of the elderly people in the 3 axes to detect the appearance of falls during their daily activities, as presented by Pierleoni et al. (2016) which implementing an embedded system with fall detection capacities allows decreasing the number of sequels caused by the fall of elderly people. Nevertheless, there are cases such as presented by Doughty et al. (2000) which describe the presence of false positives and false negatives while implementing notification systems during fall detection, being detected by systems interconnected to the network of the medical center. In these cases, the use of emerging technologies has been adopted in order to improve the detection accuracy of risk factors in the environment. In the falling detection aspects, they have selected the use of cyberphysical systems to detect risks and notify them through artificial intelligence techniques, a new tool which offers a better accuracy when notifying about abnormalities detected by the sensor with a lower probability of presenting false negatives and false positives (Pierleoni et al., 2016)(Doughty et al., 2000).

The use of Artificial Intelligence (AI) in e-Health has brought improvements in detection and risk prevention in the society. An example is the use of electronic devices combined with Cloud Computing and Fog Computing, which contain AI models focused on diagnosis and detection of chronic-degenerative diseases. Examples of this are the cases presented by Feig et al., (2017), where electronic systems were implemented interconnected with models of early detection of diabetes during the gestational period and beyond, another situation is the use of smartphones in order to provide information about the patient's blood pressure, glucose, heart rate, transmitting the information concerning the patient to a server where it is possible to visualize abrupt changes in blood pressure during the patient's activities (Shimbo et al., 2015)(Feig et al., 2017).

Another essential aspect in patient care is the temperature condition analysis where the patient performs his activities in order to prevent the emergence of diseases generated by sudden changes in temperature. In the case of older adults, the thermoregulation capacity together with the ambient temperature are essential components to prevent sudden changes in the individual's temperature (Wagner et al., 1974)(Joshi, et al., 2016)(Székely et al., 2018). An alternative to this problem is the application of domestic systems managing the ambient temperature of a given area. However, the energy saving when implementing such systems is not fully controlled, that is, in certain cases, the use of a home automation system is activated, of a specific time or in the case of presenting a change of temperature in the room even when the latter is not being occupied by any individual. Under such conditions, it is possible to provide the electronic computer vision system in order to activate and deactivate the specific electronic system of the presence of individuals in the room (Foda & Sirén, 2016)(Kotyan, Venkanna, Kumar, & Sahu, 2018).

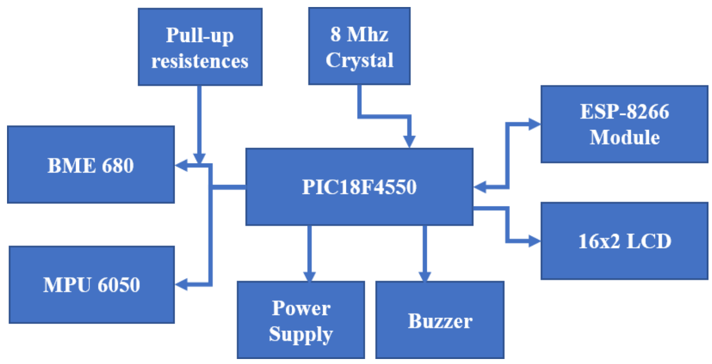
As a result, the use of an embedded system has been introduced with the capacity of monitoring a specific sector of the population, in this case the elderly people in order to detect a falling on a given space. In addition, the use of a temperature sensor integrated into the electronic system to monitor temperature conditions in the area where the individuals perform their daily activities, such information is transmitted through LAN technologies, the information is received on a web server in order to implement Cloud Computing techniques, detecting cases in which the user may present a fall or sudden changes in temperature in the environment, notifying family members or patient care personnel to execute actions against such problems.

Development

Hardware Design

The hardware system designed essentially includes 3 units responsible for monitoring, collecting and transferring information: the sensing unit, the microcontroller unit and the data transmission unit, as shown in Figure 1.

Figure 1 Block diagram of the embedded system proposed



Sensing Unit

This stage is in charge to identify the hardware to be integrated in the system for monitoring the position of the person who wear the electronic system, and identifying the component responsible for monitoring the temperature conditions in the environment of the user. The sensor to monitor the position of the individual was the InvenSense MPU-6050 sensor, this component is an inertial measurement unit (IMU) based on MEMS technology (Micro Electro Mechanical Systems), this component contains a 3-axis gyroscope and a 3-axis accelerometer (InvenSense, 2013). The data provided by the sensor are used to detect changes in the position of elderly people in a three-dimensional space. This sensor is interconnected to the microcontroller by I2C protocol. The other device responsible for monitoring environmental temperature conditions is the Adafruit' BME 680 sensor, this can monitor environmental temperature, humidity and barometric pressure. This sensor is used to transfer the information obtained through the i2C and SPI protocols (Adafruit, 2017).

Microcontroller

The microcontroller implemented in this research was the PIC18F4550, this MCU has the capacity to receive through I2C information about the positions obtained from the MPU 6050 sensor and information about ambient temperature, humidity and pressure from the BME680 sensor. This microcontroller has an LCD screen notifying the user about anomalies in the environment, in order to implement precautionary measures. Also, the electronic system integrates a speaker to emit sounds in case of fall or sudden changes of temperature. In addition, this microcontroller has an ESP-8266 for transmitting information collected through LAN.

Microcontroller - Interface module ESP-8266

The ESP-8266 module has the purpose of transmitting the information collected by the microcontroller through a LAN network (Datasheet, 2015). This module is interconnected through the pins of RC6 / TX and RC7 / RX.

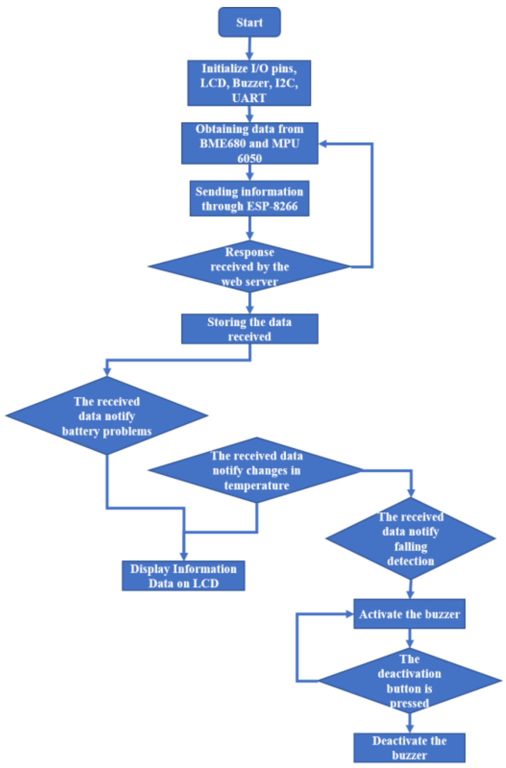
Microcontroller - LCD Interface Module

The designed embedded system has a 2x16 LCD module integrated into the D pins of the microcontroller. This component has the purpose of displaying alerts to be visualized by the elderly in case of detecting anomalies in the environment so that the individual takes precautionary measures. The interface between the microcontroller and the LCD is in 4-bit mode.

Software development

The software development includes 3 main components, one for programming and hardware operation verification and the others for the reception and development of the Artificial Intelligence model. The microcontroller programming consists of 3 phases: code writing, debugging and simulation. It was performed using the MPLAB X software. The simulation phase was carried out using Proteus software. The programming of the electronic system, as shown in Figure 2, is based on collecting information from both sensors through the I2C protocol, then the information is transmitted to the web server through the ESP-8266 module. Therefore, a waiting time is established in case of getting an answer from the web server, if the answer is affirmative, the situation will be transmitted by the web server. According to the situation received by the web server, a notification is emitted through the LCD screen or the buzzer notifying the user about the detected situation.

Figure 2 Firmware Process Flow Chart



The reception and programming stage of the Artificial Intelligence model was carried out through the Thingsboard platform and Google Colab, where the information transmitted through the LAN network was collected and the programmed model was fed through the tools provided by Google Colab.

Information gathering

The information obtained through the microcontroller is received through the Thingsboard framework, in this platform a notification system is configured in order to alert the personnel who supervises said platform and relay the information to the embedded system by emulating alerts through the horn integrated into the electronic system in case of presenting any anomaly in the individual's behavior.

The frame transmitted through the ESP-8266 to the web server consists of 3 features: the percentage of the device's battery, the variation in the X, Y and Z axes obtained from the MPU 6050 sensor and the ambient temperature, obtained by the BME 680 sensor.

Data cleaning

In data cleansing, the types of data that are being used are analyzed, as mentioned above. Body temperature sensors are used, as well as accelerometers to know the variability in the movements of elderly people. A basic statistical analysis is carried out in which the data that do not fall within regular parameters are changed by means of the clamp transformation, given by the following Formula (1):

$$a_i = \begin{cases} lowe & if\ a_i < lower \\ upper & if\ a_i > upper \\ a_i & Otherwise \end{cases} \quad (1)$$

Missing data were eliminated so as not to generate brains within the learning model (Winston & Brown, 1984).

Data Understanding

We have a real-world sample of 12277 data, which were obtained by monitoring a person, which simulated falls, violent movements, normal movements, differences in temperature, pressure and humidity, this way combinations of possible situations were made, obtaining at the end 5 different types of diagnoses (population) for the possible environment where the person is.
The data used are:

Table 1 Information sent to Thingsboard platform

Battery percentage
Variation in axes
Environment temperature

Once the data are clean, a normality test is performed to analyze the data with specialized statistical techniques, such as ANOVA.

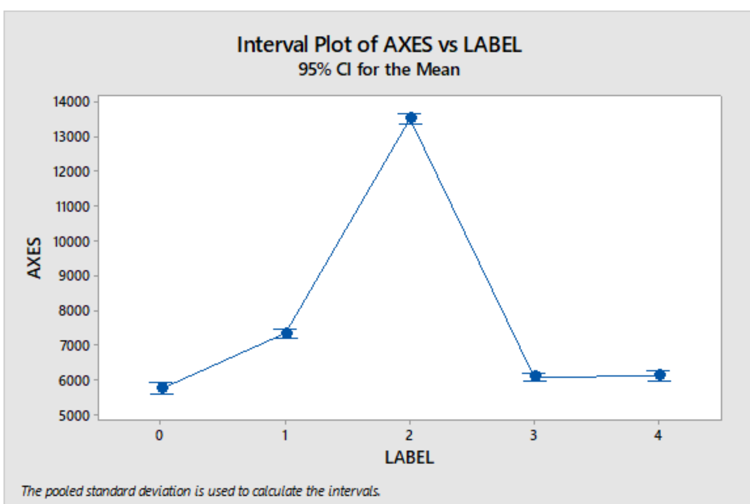
ANOVA Analysis

The ANOVA assess the importance of one or more factors by comparing the means of the response variable at the different levels of the factors. The null hypothesis establishes that all population means (factor level means) are equal while the alternative hypothesis states that at least one is different.

Therefore, for the current problem, it is sought to perform an analysis of variance in conjunction with a Fitcher analysis and determine if any of the labels belong to the same population as another, with the aim of reducing the computational load of the learning algorithm (Sugiyama, 2007). Based on the foregoing, the hypothesis is established as follows in Formula (2):

$$\begin{aligned} &X \leftarrow \text{All means are equal with respect to labels} \\ &Y \leftarrow Not \text{ all means are equal with respect to labels} \end{aligned} \quad (2)$$

Figure 3 ANOVA analysis of the dataset



See Figure 3, the 95% variability in the confidence interval of the AXES characteristic against the dependent variable, then Figure 4 shows the p-value is less than 0.05, therefore, the null hypothesis is rejected and concludes that there is a significant variation between the labels.

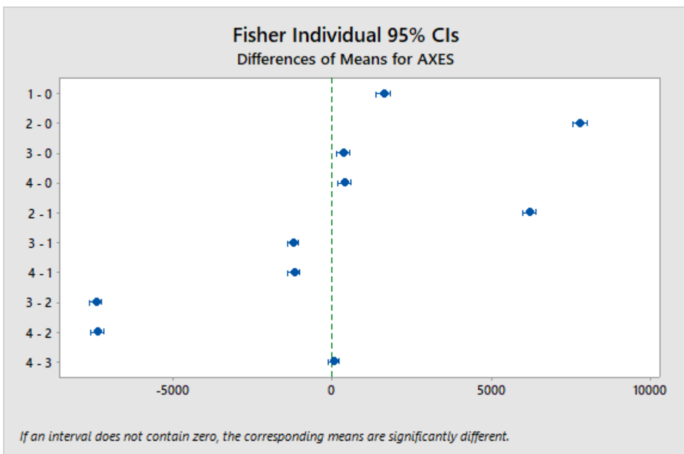
Figure 4 Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
LABEL	4	88169559804	22042389951	1945.03	0.000
Error	12272	1.39074E+11	11332652		
Total	12276	2.27244E+11			

Fisher Analysis

It is used to examine the significance of the association (of contingency) between the two types of classification, in other words, it allows reducing the number of populations Figure 5.

Figure 5 Fisher analysis of the dataset



In the case of the current project labels, and thus maximizing the learning of the artificial intelligence technique, see Figure 6 where it is verified that label 3 and 4 are significantly equal, therefore, only 4 labels are available

Figure 6 Fisher pairwise comparisons

Grouping Information Using the Fisher LSD Method and 95% Confidence

LABEL	N	Mean	Grouping			
2	1945	13533.6	A			
1	2341	7351.1		B		
4	2042	6125.9			C	
3	4380	6089.1			C	
0	1569	5760.8				D

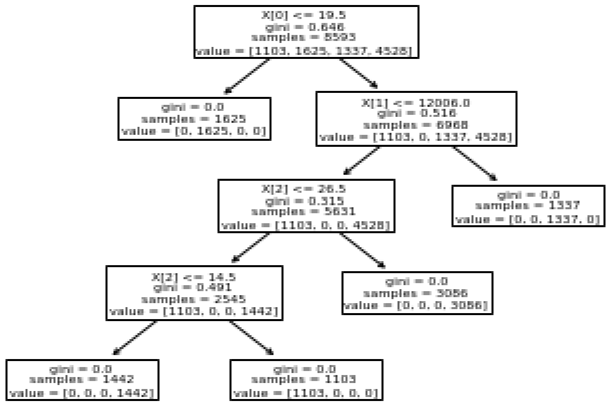
Means that do not share a letter are significantly different.

Modeling

A decision tree is a decision support tool that uses a tree-shaped chart or decision model and its possible consequences, including the results of fortuitous events, resource costs and utility (Géron, 2017). It is a way of displaying an algorithm that only contains conditional control statement.

See the Figure 7 where it is modeled with respect to the proposed data, this technique was used due to the small dimensions of the dataset, if working with a larger set of features it is very likely to require more robust techniques

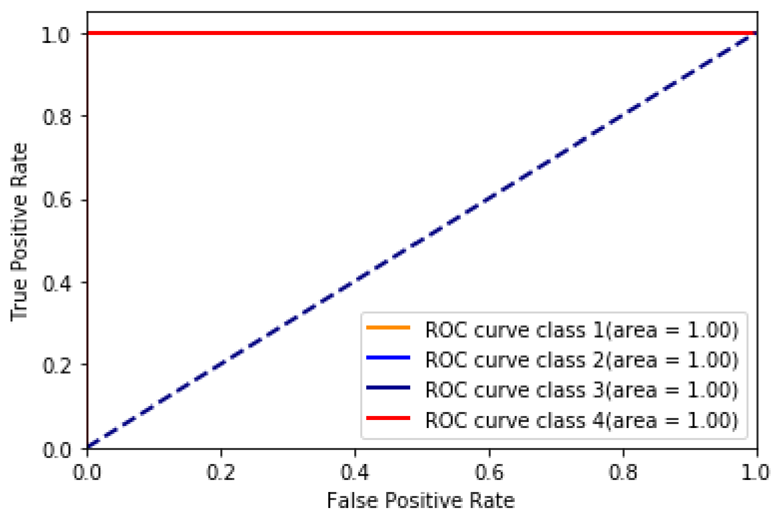
Figure 7 Dataset trained by Random Forests



Results

A commonly accepted way to evaluate supervised learning algorithms using Receive Operating Characteristic curves (ROC curves), these curves assess how specific a model is against how sensitive it is. In this situation the model used for train and test with the dataset provide by the embedded system can provides a better detection in falling and checking the environmental temperature. This model provided a X% of accuracy and the transmission of its response could help to the elderly people or medical personnel about problems caused by a falling or an abrupt changes in the environmental temperature.

Figure 8 Dataset ROC Curves



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Conclusions

The use of IoT and AI in dailylife provides a better response in healthcare. In this situation IA techniques were implemented along with the implementation of an embedded system with capacity to monitor falls and ambient temperature providing medical staff, patients or relatives of the patient the ability to know in real time the patient's situation. In this case, communication is implemented between the sensors responsible for monitoring environmental conditions and the patient through I2C communication. The information is transmitted via LAN to Thingsboard platform. This platform sends the information to the Google Colab platform in order to provide a better prediction about the situation obtained from the sensors integrated to the electronic system. The result of the analysis on this platform is re-directed to the Thingsboard platform and, as a result, is transferred to the microcontroller in order to notify to the medical staff or patient about the detected anomaly.

A future proposal to improve in future projects is the implementation of a platform responsible for the reception and transmission of information with the ability to perform the analysis of the monitored conditions without the need to retransmit that information. In addition, it is necessary to provide more information to the training of the proposed model than was provided during this research.

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