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# An Architecture for an IoT-based Telecare System for the Elderly Using Big Data Analytics

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**Abstract.** The accelerated aging of the population is a real and constant situation worldwide. Long-lived population is the most affected demographic sector in terms of health and home safety. The advent of Big Data, in conjunction with the Internet of Things (IoT) omnipresence, have made telecare-based systems an increasingly desirable alternative when dealing with the treatment and remote care of the elderly and frail, allowing them to go on with their lives in a normal, almost independent manner. This situation has spawned an ever increasing demand for innovative telecare solutions. In order to present an alternative solution to the problem at hand, this paper proposes a telecare system architecture based on IoT and Big Data Analytics (BDA) to monitor the user's vital signs and activities, send alerts to the caregivers whenever necessary, with the goal of detecting and preventing accidents in the home.

**Keywords:** big data analytics, internet of things, telecare, wearable, decision tree.

## 1 Introduction

The impact of BDA techniques in healthcare organizations shows promising research directions, especially when implementing novel use cases for potential healthcare frameworks. Over 10 million people in Mexico are 60 years of age or more, frequently spending long periods of time alone at home; which increases the probabilities of going through a medical emergency while on their own.

**Table 1.** Comparative analysis of related papers.

| Authors | Usage of sensors or wearables | Prevention | Big Data Analytics | Contribution |
|---|---|---|---|---|
| Yacchirema et al. [1] | Both | × | ✓ | System for the detection and support of treatment of Obtrusive Sleep Apnea of elderly people |
| Yacchirema et al. [2] | Both | × | ✓ | A decision tree-based Big Data model for fall detection |
| Jankowski, Schönijahn and Wahl [3] | None (computer vision) | ✓ | × | Research on tele-monitoring |
| Khalifeh et al. [4] | Sensors | × | × | Build an e-health monitoring and fall detection system |
| Meissner [5] | Both | × | × | Build a fall detection system that monitors in real-time an older adult |
| Silapachote et al. [6] | Both | × | × | Fall detection and response tracking application |
| Walters et al. [7] | Sensors | × | × | Design and test modules of a monitoring system based on multiple sensor feedback in a bathroom setting |

Two main approaches for this type of problem were identified during the analysis of the literature, namely, computer vision techniques using image-recognition and streaming, and a sensor-based approach using wearable devices to monitor the user's physical health.

All telecare systems proposed in the literature focus on the detection of accidents, while ours focuses on preventing them using predictive analysis; a rule-based classification algorithm was implemented using a decision tree as part of the architecture proposed in this paper, hinging on the use of IoT devices and BDA techniques to prevent possible accidents in the home.

After carrying out the case study, it was found that the use of big data analytics on data coming from wearable devices provides a viable solution to the problem stated, making it possible to send notifications to any interested party, alerting about changes in the user´s physiological parameters which could result in a dangerous, and otherwise unforeseen, situation, allowing caregivers to act accordingly and in a prompt manner.

The rest of the paper is distributed as follows. Section 2 contains a comparative analysis of related work in the field of IoT and BDA in telecare systems. In section 3, the system's architecture and its modules are described. Section 4 presents a case study, and finally, conclusions and future work are included in section 5.

## 2 Related Work

Table 1 shows a concise description of the most relevant features of the scientific papers included as related work.

As shown in Table 1, using wearable sensors as a data source for innovative telecare systems for fall detection and indoor monitoring of frail or elderly people, is an approach which constantly gains preference in IoT and/or Big Data contexts. The telecare systems proposed by the authors focus primarily in the detection of a falls, using sensors [4, 7], as well as wearables [1, 2, 5, 6], while [3] presents a research on tele-monitoring for the prevention of accidents. In this aspect our work differs from the rest in that it proposes a telecare system architecture to prevent accidents in the home by monitoring physiological parameters obtained via a wearable device and using them in conjunction with the user's age and gender to send alerts when a set of irregular values are recorded during a relatively short period of time.

Our architecture is comprised of several modules. Data will be retrieved through constant monitoring of a wearable device manufactured by Fitbit Inc., through its API endpoints. All collected data will be stored in the non-relational database management system *Apache Cassandra*™ and fed to an *Apache Spark*™ cluster for analytical purposes, with the goal of preventing accidents in the home, generating alerts and notifications sent to the user's caregivers and family members via mobile and web applications.

## 3 Architecture

Fig. 1 shows the proposed multi-tiered architecture and its modules. The function of each module is briefly described below.

### 3.1 IoT Layer

**Data acquisition module.** Data is periodically collected through Fitbit's API endpoints in JavaScript Object Notation format, including, but not limited to, the user's vital signs, burned calories and physical activities, allowing the system to assess, to a certain extent, the user's physical health and whether or not there is a potentially dangerous situation, alerting the caregivers and family members accordingly.

### 3.2 Storage Layer

**Big Data repository.** Data coming from the IoT layer will be stored in a Cassandra database cluster, which will serve as a data frame provider for the classification algorithms run in the Spark cluster.

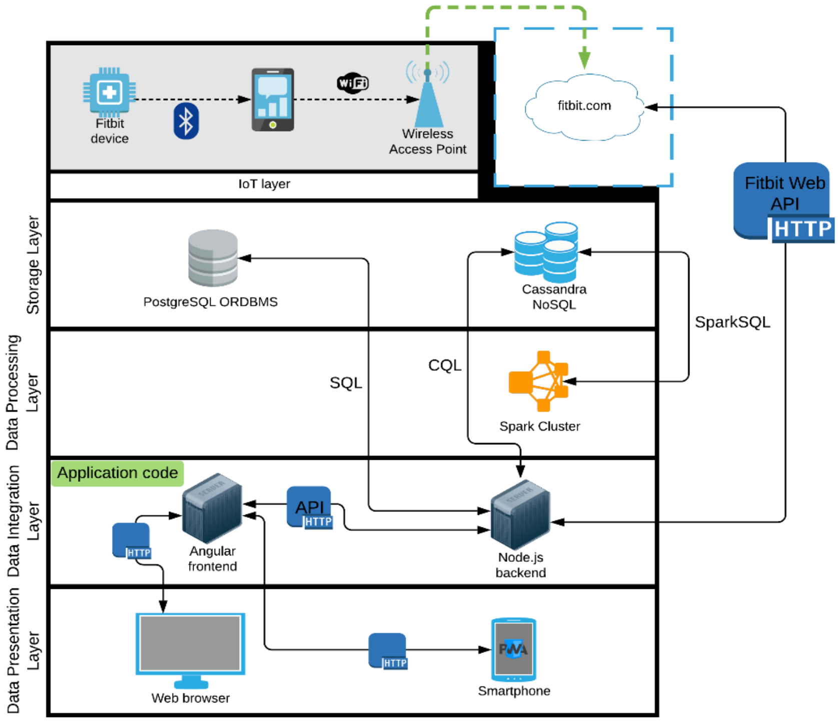


**Fig. 1.** Architecture.

**PostgreSQL repository.** The PostgreSQL Object Relational Database Management System will be used to store any information, which does not come from the IoT layer, thus not being used in any Big Data Analytics process, but still needed for the complete functioning of the system.

### 3.3 Data Processing Layer

This layer contains the Spark cluster, in which machine learning algorithms will be carried out, using a predictive model designed to detect patterns and anomalies in the user's physical health and activities, with the purpose of preventing accidents. Parameters like sleep status, heart rate levels and physical activity, the latter in the form of walked distance or steps taken, will produce the input variables for the algorithms, and the result will be a notification or alert of the elder's condition.

### 3.4 Data Integration Layer

**Backend module.** All data collected will be transmitted via web services and into the applications' backend module in the Node.js server. The server will persist the data in

| Date | Out of Range | Fat Burn | Cardio | Peak |
|---|---|---|---|---|
| 2019-09-14 | 721.55 cal.<br>529 min. | 251.06 cal.<br>77 min. | 0.00 cal.<br>0 min. | 15.19 cal.<br>1 min. |
| 2019-09-13 | 392.57 cal.<br>277 min. | 2,929.92 cal.<br>743 min. | 97.68 cal.<br>10 min. | 42.97 cal.<br>3 min. |
| 2019-09-12 | 1,070.04 cal.<br>741 min. | 1,332.58 cal.<br>492 min. | 33.71 cal.<br>4 min. | 0.00 cal.<br>0 min. |
| 2019-09-11 | 1,023.86 cal.<br>755 min. | 1,694.78 cal.<br>525 min. | 579.42 cal.<br>58 min. | 36.80 cal.<br>3 min. |
| 2019-09-10 | 1,289.98 cal.<br>877 min. | 1,459.28 cal.<br>499 min. | 415.67 cal.<br>47 min. | 75.58 cal.<br>6 min. |
| 2019-09-09 | 1,190.57 cal.<br>755 min. | 2,163.67 cal.<br>626 min. | 48.66 cal.<br>5 min. | 0.00 cal.<br>0 min. |

| Time | Heart rate |
|---|---|
| 01:31:00 | 95 |
| 01:32:00 | 93 |
| 01:33:00 | 92 |
| 01:34:00 | 92 |
| 01:35:00 | 94 |
| 01:36:00 | 94 |

**Fig. 2.** Heart rate information as it is presented in the web application.

Cassandra for later processing, and, in occasions, will also send it directly to the frontend module to be presented to the applications' users. This distinction is made according to what triggered the data transmission process, an alert from the system or a normal request from the user.

**Frontend module.** The frontend module will only make requests directly to the backend, retrieving all required information to be shown to the users in the presentation layer via the web and mobile applications.

### 3.5 Data Presentation Layer

Information like reports and records will be constantly accessible to caregivers and family members through the web and mobile applications. Alerts and notifications will be sent according to the results obtained from the algorithms executed in the backend and data processing modules. Such events will be triggered as a consequence of a dangerous situation being detected by the system, or an accident which already occurred and requires immediate action on behalf of the applications' users, namely the relatives and wardens.

## 4 Case Study

A rule-based classification algorithm was implemented using a decision tree. The algorithm uses the data coming from the Fitbit device, namely the user's age, sex and heart rate. Fig. 2 shows two tables with heart rate data, one contains daily aggregates (left), and the other, a per-minute representation (right) of the date corresponding to the highlighted row, as it is presented to the user in the web application.

Fig. 3 illustrates a graphical representation of the algorithm, a sample input for a given instance of time, and the resulting information shown to the user; input

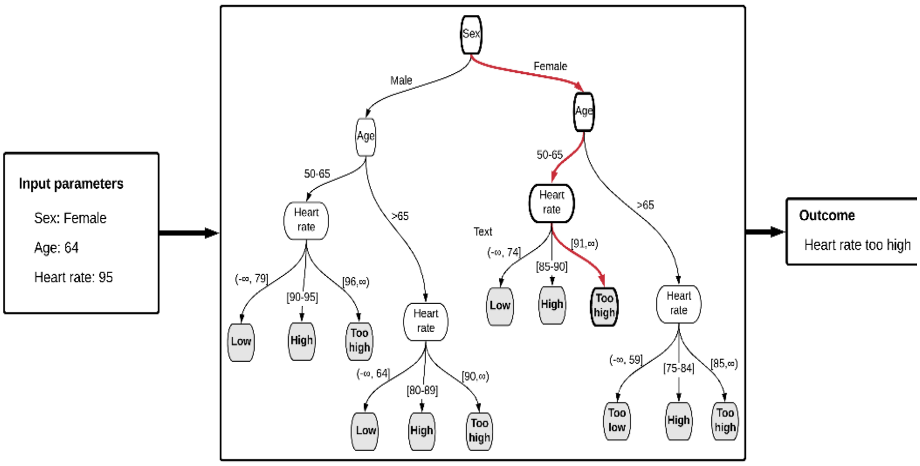


**Fig. 3.** A graphical representation of the algorithm.

parameters correspond to a 64-year-old female subject, whose heart rate, at a given instance of time, is 95, which is considered too high for this input set.

One abnormal value is not a direct indicator of a problem, for example, the simple action of standing up can cause a temporary surge in heart rate, even more when dealing with older persons, which is why the alert is not sent on every abnormal value detected. Heart rate data is requested every ten minutes to the Fitbit Web API, containing values from the last time data was received until present time, the algorithm then executes using the dataset corresponding to the last hour; results are then grouped for every five consecutive minutes, and if in any of those groups, abnormal values represent at least 80%, a notification is sent to the caregivers, so they are aware of the situation and are able to take appropriate actions.

## 5 Conclusions and Future Work

The continuous aging of the population, alongside the increase of chronic diseases, can cause home accidents to occur more frequently, especially when involving the elderly; this situation can be tackled effectively through the development and installation of telecare systems, taking advantage of the usage of wearable devices, sensors and surveillance devices, and by harnessing the computing capabilities of BDA tools. Taking this into consideration, a BDA and IoT based telecare system was proposed in this paper, to monitor the user’s vital signs, and send alerts on potentially dangerous situations, with the goal of preventing accidents in the home. Our case study verified the effectiveness of the decision tree approach as part of the architecture to prevent accidents in an indoor environment, quickly making caregivers and family members aware of the situation.

Future work will include the expansion of the model used in the decision tree as part of a new iteration of the KDD (Knowledge Discovery in Databases) process, because the current one, although effective in the detection of abnormal heart rate values on a per-second basis, can be improved by using additional parameters, such as age, weight, sleep status and steps taken in a period of time; the goal is to factor the user's physical and mental exhaustion into the algorithm, which would yield more accurate predictions regarding a possible fall.

Also, a data source will be added in the IoT layer, in the form of a Computer Vision module, comprised of a camera device, attached to a Raspberry Pi B+ board. A computer vision software will be programmed using OpenCV, and will be installed in the board. This module will add up to the wearable's input in the data acquisition process, this time including the objects layout as well as the elder's position in the room. A prediction model will be designed and implemented in Spark, which, with the added data source, would effectively increase the accuracy of the predictions.

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