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Fall detection system for elderly people using IoT and Big Data

Diana Yacchirema[a,b,*], Jara Suárez de Puga[a], Carlos Palau[a], Manuel Esteve[a]

[a]*Universitat Politècnica de València, Camino de Vera S/N, Valencia, 46022, Spain*
[b]*Escuela Politécnica Nacional, Ladrón de Guevara E11-253, Quito, 17-01-2759, Ecuador*

Abstract

Falls represent a major public health risk worldwide for the elderly people. A fall not assisted in time can cause functional impairment in an elder and a significant decrease in his mobility, independence and life quality. In that sense, the present work proposes an innovative IoT-based system for detecting falls of elderly people in indoor environments, which takes advantages of low-power wireless sensor networks, smart devices, big data and cloud computing. For this purpose, a 3D-axis accelerometer embedded into a 6LowPAN device wearable is used, which is responsible for collecting data from movements of elderly people in real-time. To provide high efficiency in fall detection, the sensor readings are processed and analyzed using a decision trees-based Big Data model running on a Smart IoT Gateway. If a fall is detected, an alert is activated and the system reacts automatically by sending notifications to the groups responsible for the care of the elderly people. Finally, the system provides services built on cloud. From medical perspective, there is a storage service that enables healthcare professional to access to falls data for perform further analysis. On the other hand, the system provides a service leveraging this data to create a new machine learning model each time a fall is detected. The results of experiments have shown high success rates in fall detection in terms of accuracy, precision and gain.

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Keywords: Fall detection; Internet-of-Things; Big Data, 6LowPAN; wearable sensor; Smart IoT Gateway; fall detection; decision tree learning algorithm; accelerometer; elderly people.

1. Introduction and related works

Life expectancy has increased by a rate of five years since 2000 due to advances in the medical field. According to the World Health Organization (WHO), by 2050, the current population of elderly people (8.5%) will increase, representing 20% of the world's population [1]. On the basis of these trends, many countries are adopting healthy

* Diana Yacchirema. Tel: +00(34)640072098.
E-mail address: diayac1@doctor.upv.es

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aging policies with the aim of helping elderly people lead an active and independent life [2]. In particular, ensuring active and healthy aging (AHA) of the elderly people is one of the greatest challenges, but also a great opportunity for society in the coming decades. The notion of AHA has been lately characterized as a broad concept, which seeks to improve the quality of life (QoL) of the elderly people as they age, optimizing opportunities for health, participation and security [2]. In that sense, health problems of the elderly people have become increasingly urgent and falls are the most common accidents whose severity may often require medical attention. According to the WHO, approximately 30% of the people over 65 suffer accidentally one or more falls per year, and for the people over 80 years this rate increases to reach 50%. This figure is more alarming if one considers that falls often happen in indoor environments and are related to normal activities of daily living (ADL).

A serious consequence of suffering a fall is the "long lie", which consists of remaining on the ground for long periods of time until help arrives [3]. The "long lie" can lead to serious health complications, including dehydration, pneumonia, and hypothermia, which in many cases, can lead to death within 6 months after a fall. Therefore, a fall not assisted in time in an elderly person can negatively impact their QoL and independence [4]. In this context, IoT systems that contribute to detect falls and alert emergency services on time are a social need.

At present, several solutions have been proposed for elderly fall detection. Such solutions are categorized [4] into three main types according to the sensor-technology used: Non-Wearable Based Systems (NWS), Wearable Based Systems (WS), and Fusion or hybrid based Systems (FS).

In particular, NWS systems that use vision based devices such as [5] [6] [7] has been proven to be powerful and robust for detecting falls. However, the main disadvantage of these systems is their high cost and consequent lack privacy for elderly people due to these systems require that the sensors need to be strategically distributed in the indoor environment in which the elderly lives. To overcome this limitation, WS systems like [8] [9] [10] has been proposed, which usually employ inertial sensors such as accelerometers and gyroscopes, typically attached to the body of the elderly for movement recognition when a fall takes place. In particular, accelerometers are being used increasingly in WS systems because they offer advantages such as low power consumption, low cost, low weight, ease of operation, small size, can be mounted on the various body locations and, most importantly, portability. As a result, one of the most commonly used method for fall detection involves the use of a tri-axial accelerometer along with a threshold-based algorithm, which has been used by some representative works [8] [9] [10]. These works detect a fall when the acceleration coming from a tri-axial accelerometer embedded in a wearable device is out of the set threshold. One of the biggest advantages for using the threshold-based methods is less complexity and computation cost compared to other methods. However, finding an appropriate value for the threshold that allows detecting all type of falls without getting confused with some ADL, has proved to be a complicated problem.

Recently, WS systems based on machine learning (ML) techniques has been proposed to deal with these disadvantages and improve accuracy in detecting falls. ML is a technique in computer science that involves statistical inference of models from data in order to make automated predictions. ML builds a model from training data to predict or solve the given problem. In several works, authors focus on use some ML techniques for fall detection. For example, Mezghani et al. [11] used the non-linear support vector machine technique to extract the features and obtain meaningful from the human body data captured by an accelerometer attached to a smart textile. Since it needs two feature extractions: the first to identify the peak and the second to detect the fall orientation, it requires more processing compared to the algorithms carrying out an only extraction. By extracting time series from human motion retrieved by a tri-axial accelerometer placed at human upper trunk Tong et al. [12] used hidden Markov model (HMM)-based method to detect and predict falls. The experiment results show an ideal success rate in the fall detection (100% sensitivity and 100% specificity). However, for training and setting the HMM (λ) and thresholds of the system, data samples of young people's simulated activities were used. In addition, this system does not alert when a fall event occurs. Finally, Aguiar et al.[13] used a smartphone built-in accelerometer for continuously monitoring of the movement's data of elderly people. These data were used to test offline three different learning classifiers: Decision Trees, K-Nearest-Neighbours (KNN) and Naive Bayes. The results show that the decision-trees-based algorithm presented the best performance, with more equilibrated sensitivity and specificity values compared with the other tested algorithms. Nevertheless, as a result of the relatively high energy consumption of smartphones, this system could only be active for a short period of time. The decision-tree-based algorithms is gaining acceptance and is probably the best approach to increase the accuracy and precision for the fall detection. We have followed a similar approach in this paper by using a decision trees-based Big Data model for fall detection, but we differ from previous works in the way the system is built. First, the data from the movements of elderly people in the indoor environment is captured by a 3D-axis accelerometer embedded into a 6LowPAN device wearable. Second, the fall of an elder is detected by a decision trees-based Big Data model which is built and training in the cloud. Initially, it is trained from historical knowledge from an open dataset that containing records of falls and ADL of elderly people. Subsequently, the model learns of the fall events detected by the system. One of the main innovations of the model is that runs on a resource-constrained device, a Smart IoT gateway which provides fog computing capabilities that enable fall-detection related processing locally in order to reduce the time of "long lie". When a fall is detected, the Smart IoT gateway is capable of sending notifications, with information of the fall type and location of elderly person's house, to healthcare professionals through a lightweight and secure IoT protocol. In addition, the Smart IoT Gateway also provides interoperability and data transformation to allow the system to integrate in a holistic way with other AAL systems or IoT Platforms. Finally, the fall events detected are stored in the cloud to give more accurate information to healthcare professionals. Additionally, this data are used to build a new model every time a fall is detected, which is subsequent instanced at the Smart IoT Gateway. The performance of the FD-system has been confirmed in terms of accuracy, precision and gain.

Following this introduction, this paper is organized as follows. In Section 2, the FD-system and its constituent components are described. Following, in Section 3, the experimental results and evaluations are presented. Lastly, conclusions and future work are described in Section 4.

2. Fall detection system architecture

The FD-system proposed, show in Fig.1, consists of four main components: A wearable device, a wireless communication network, a Smart IoT gateway and Cloud services. Each component plays an important role in the detection of falls.

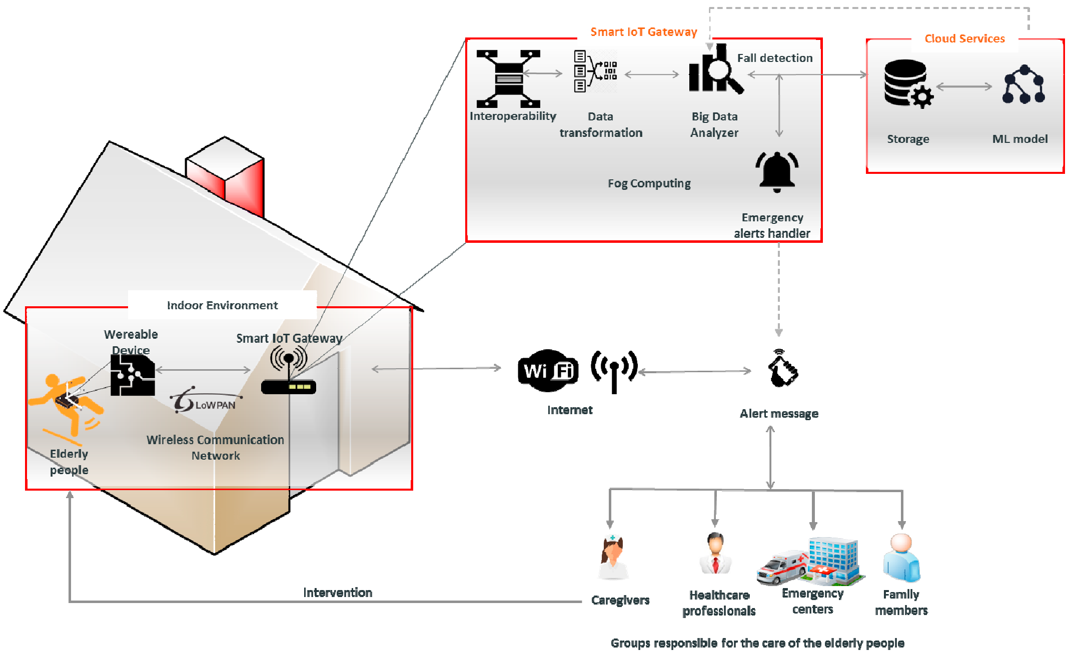

Fig. 1. The FD-system overview

2.1. Wearable device

A prototype of the wearable device was constructed from the combination of three modular blocks: NUCLEO-L152RE, plugged with one expansion board (X-NUCLEO-IDS01A5) with sub-1GHz RF connectivity operating at 868 or 915 MHz and a sensor expansion board (X-NUCLEO-IKS01A1) developed by ST Microelectronics. The NUCLEO-L152RE is equipped with an ARM 32-bit Cortex-M3 processor designed to offer very high performance, digital signal processing with low power and low voltage operation. The sensor board consists of several tiny-ultralow-power sensors. However, only the MEMS motion sensor (LSM6DS0) is used for gathering the motion data that take place when the adult is falling or performing ADLs. LSM6DS0 is 3D-axis accelerometer which operates with a full-scale acceleration range (±2/±4/±8 g).

The wearable device firmware is based on 'Contiki', an open source operating system (OS) developed for constrained networks. By using the Contiki OS, we get full IoT stack support over 6LowPAN, in other words, 6lowPAN, RPL (IPv6 Routing Protocol for Low-power and Lossy Networks) and CoAP (through Erbium) support. Erbium is a low-power REST engine written in C language that provides RESTful access to the resources of the wearable device.

Furthermore, the REST paradigm, inherent in the constrained application protocol (CoAP), has been exploited. CoAP is a lightweight IoT protocol which shares similarities with HTTP since it includes resource abstraction, URI use, RESTful interaction (i.e., methods such as GET, POST, PUT, and DELETE to access the various resources), and extensible header options [14]. However, compared with HTTP, CoAP implementation uses minimal resources on the constrained devices and the constrained networks. Hence, it suitable for constrained environments in IoT.

A CoAP Server is built in the wearable device for reading the accelerometer' measurements. The measurements are periodically retrieved using the CoAP GET method on the respective resource path including the IPv6 address and port of the CoAP Server as shown in the table 1.

Table 1. Acceleration Resource and Associated CoAP Path

Parameter	Description
Sensor	LSM6DS0
Resource	Acceleration
Resource path	GET [coap://[aaaa::b00:f6ff:2d3b:d2c4]:5683/sensors/acceleration

2.2. Wireless Communication Network

The wireless communication between devices and the Smart IoT gateway is established by the low-power wireless IPv6 (6LowPAN) technology based on the IEEE 802.15.4 standard. 6LoWPAN is a technology designed for supporting the connectivity, interoperability and compatibility of heterogeneous WSNs at a very low cost and with very low requirements compared with other technologies such as Wi-Fi or Bluetooth. In addition, this technology has inherent advantages; greater mobility, bigger address space, easy deployment and maintaining, what makes this technology suitable to be used in IoT-enabled devices, especially in resource-constrained devices.

We build and deploy a 6LoWPAN network composed of two 6lowPAN nodes: a wearable device and a 6lowPAN Border Router (6LoBR). 6LoBR plays an important role in communication inside and outside of our 6LowPAN network. The 6LoBR is responsible of (i) exchange data between wearable device and cloud services and (ii) provide forwarding and routing capabilities inside the 6LoWPAN network. In this work, the Smart IoT gateway plays the role of 6LoBR.

2.3. Smart IoT Gateway

Smart IoT Gateway is the key component for fall detection and consists of four modules: interoperability, data transformation, big data analyzer, emergency alerts handler.

2.3.1. Interoperability: Smart IoT Gateway acts as a bridge between 6LowPAN network and cloud services, thus enabling the connectivity and seamless communication between all the system's components. It provides protocol conversion functions that include 6LowPAN transition mechanisms - IPv6 / IPv4 and message translation between CoAP and MQTT protocols.

2.3.2. Data transformation performs two functions. On one hand, it receives the movement data (x, y and z acceleration values) and performs filtering using a first order IIR low-pass filter, and, on the other hand, it annotates and maps data in a comma-separated value (CSV) file format. Each filtered acceleration value is stored locally to be used as input to the big data analyzer module.

2.3.3. Big Data Analyzer is responsible for processing and analyzing acceleration values in the x, y and z axes to detect if these values represent a fall. Prior to detection the falls, we started by created and trained a classification model based on decision trees from the knowledge of past events (falls data). These steps are executed in the cloud. Historical knowledge is essential to understand what behavior is expected. For example, using knowledge of the behavior of unexpected motion patterns that have occurred when an adult falls, will enable alerts and predict situations of risk when similar patterns of behavior occurs. The falls detection involves three steps illustrated in Fig.2, and described in more detail in the following text.

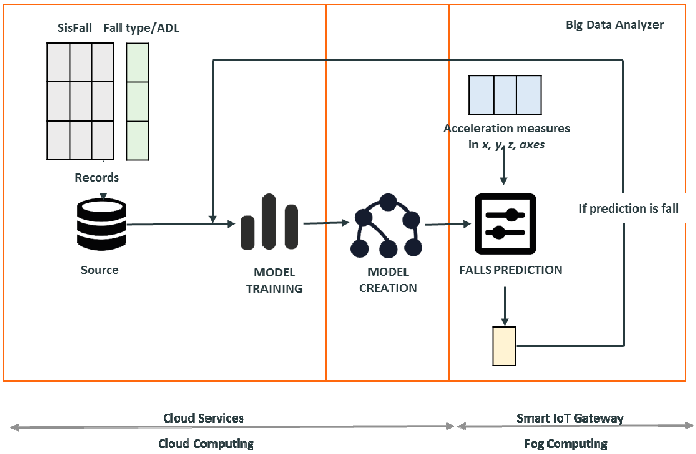

Fig. 2. Fall detection method steps

- *Step 1 Model creation:* A decision trees-based model is built from SisFall dataset[15] (detailed below). The decision tree is widely used for data classification, and it is one of the best methods of classification and regression amongst many other algorithms as it uses a non-parametric structural design which makes it effective for handling large size datasets without the overfitting problems very common in other ML algorithms. In addition, decision trees can be easily converted to classification rules[16]. We use BigML Data Analysis tool [17] to create the model. BigML is a software-as-a-service to ML, designed to create predictive models and embed them into software applications by RESTful APIs.

- *Step 2 Model training*: In our work, the SisFall records are used initially to train the model. Subsequently, the model learns of the fall events detected by the Smart IoT Gateway. SisFall is a set of publicly available data for benchmarking and developing of fall detection systems. This dataset contains records from 38 participants, of which 15 are elderly persons aged between 60 and 75 years old. All elderly participants' simulated activities of ADLs and only one of these participants simulated both falls and ADLs, who is an expert in Judo. The signals were captured in laboratory experiments using three inertial sensors (2 accelerometers: ADXL345 and ITG3200, and 1 gyroscope: MMA8451Q) integrated in a self-developed embedded device. Both acceleration and gyroscope signals were acquired with a sampling rate of around 200 Hz. The elderly participant performed 19 types of ADLs and 15 types of fall. In this work, 3 types of fall are detected, which are shown in the Table 2. In our system, the training dataset used to create the model includes 955 ADLs records and 2865 falls records captured by the ADXL345 accelerometer. This data represents specifically the changes of acceleration (peaks) produced by the falls.

Table 2. Falls of SisFall used in this work.

Code	Description
F1	Fall forward while walking caused by slip
F2	Fall backward while walking caused by slip
F3	Lateral fall while walking caused by a slip

Once the model has been trained, it classifies the event as a fall or as ADL. Fig.3 (a), illustrates the results of the classification of the decision tree. This indicates how important each variable (acceleration measures in the *x*, *y* and *z*, axes) is in fuzzy decision-making capabilities (prediction) of fall types and of the ADLs. Each node represents a classification rule (i.e., IF-THEN rule) to a variable. Branches leading from the node indicate the path(s) that could be taken. Each path has a confidence level associated with it (show Fig.3 (b).). The thickness of the branches indicates the amount of training data that this path undertook. The leaf node constitutes the decision based on a prediction. Acceleration data are in bits and they could be converted into gravity following the equation described in the supplementary materials of SisFall available online[18].

- *Step 3 Falls Prediction:* In order to fall detection, the big data analyzer creates a local instance of the model**.** The predictions are created and computed taking as input data the information coming from the transformation module by using the REST APIs provided by BigML. If the result of prediction is a fall, the system invokes to the emergency alert handler and send the falls data to the cloud services.

2.3.4. Emergency alerts handler sends notifications of the fall event along with the GPS position of elderly person's house to the groups responsible for the care of the elderly people previously registered in the system using a MQTT-broker. The Fig.4 shows an example of the notifications sent. This information also is sent to the cloud services. MQTT is chosen because it is a lightweight and secure IoT protocol. MQTT provides end-to-end secured communication and reliability based on SSL. In addition, it incorporates several levels of quality of service to confirm the delivery of messages, from a non-optimal minimum level (QoS0) to a double-recognition level (QoS2). Since our system is closely related to the elderly's healthcare, the level of the quality of service QoS 2 has been configured to guarantee the reliability of the delivery of the messages.

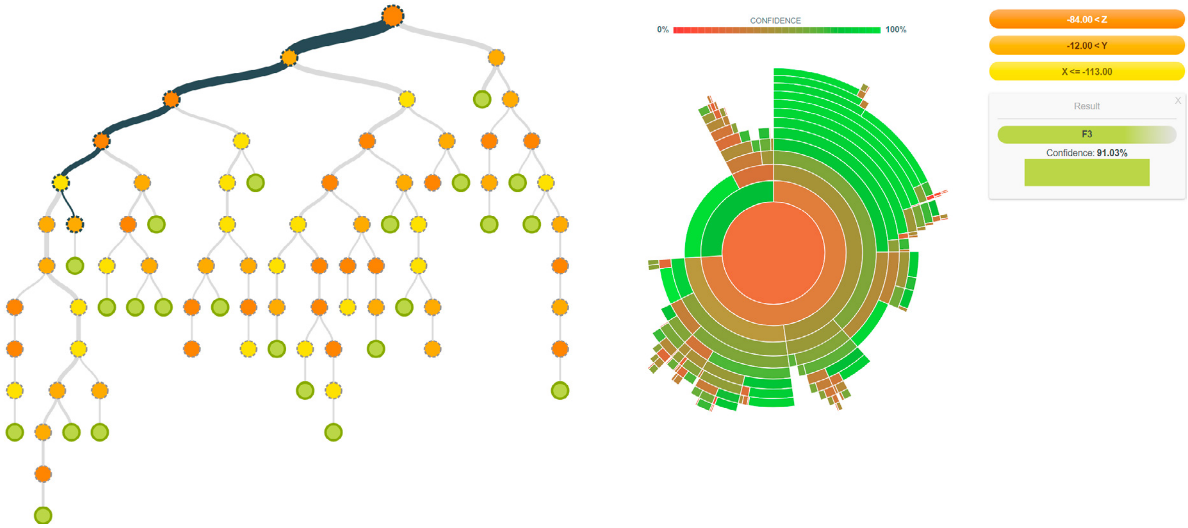

Fig. 3. (a) Model classification, (b) Example of the confidence of a type of fall.

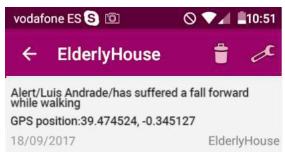

Fig. 4. Example of a notification sent to the family caregiver

The Smart IoT Gateway is formed by the combination of STM32 Nucleo board (NUCLEO-L152RE) integrated with one expansion boards (X-NUCLEO-IDS01A5), and a raspberry Pi 3 equipped with a 1.2 GHz Quad-Core ARM Cortex processor, 1GB of RAM and extensible storage, 4 USB ports, 1 HDMI port, 1 RJ-45 port and one power consumption of 700 mA, (3.5 W). We use a 32 GB class 10 SD card powered by the Raspbian operating system in order to execute the functionalities of all modules of Smart IoT Gateway. In addition, the raspberry Pi board is connected to an Ublox NEO-6M GPS module, this allows tracking the location of elderly' house.

The STM32 Nucleo board (NUCLEO-L152RE), along with one expansion board (X-NUCLEO-IDS01A5), define the 6LoBR node, which collect data from wearable device and forward to the raspberry Pi through a USB serial link. Similar to the wearable device, all operations in the 6LoBR node are executed on 'Contiki' OS. To enable communication between 6LoWPAN nodes and Smart IoT Gateway, RPL is configured. On the other hand, to translate packages coming from 6LoWPAN nodes to IPv6/IPV4 packages and vice versa, a tunnelling-virtual network adapter is configured in the Raspberry Pi by using tunslip6 tool running on Contiki OS. Additionally, to retrieve the acceleration values of the wearable device, a CoAP client is implemented in Raspberry pi using aiocoap library based on Python 3 asynchronous I/O.

2.4. Cloud Services

Cloud Services receive the falls information from Smart IoT Gateway and store them using MongoDB. Once a fall occurs, the model is again created and trained in the cloud using the API REST of BigML, for its subsequent be locally instantiated in the gateway.

3. Results and Evaluations

For evaluation of the proposed system, a total of 12 controlled experiments were performed: 9 experiments of falls and 3 experiments of ADLs. Three subjects (volunteers) between the ages of 40 and 60 participated in the experiments. The wearable device was placed on the volunteers' waist. The falls were simulated in no particular order. Initially, several tests were performed to tune the system parameters. The results obtained after the experiments are analyzed using various statistical parameters like Accuracy, Precision, Gain or Recall. These parameters are defined by concepts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad \Pr ecision = \frac{TP}{TP + FP} \qquad Gain = \frac{TP}{TP + FN}$$

Terms true and negative are used to refer to the presence or absence of the condition of interest, fall. True positives are the main instances of interest while true negatives are all other instances. The table 3 show confusion matrix, which lists the evaluation results of the proposed system for three types of falls and one activity (i.e., walking upstairs and downstairs slowly activity) referred to as A1.

Table 3. Confusion matrix obtained by detection model

	Targets					%Gain
	A1	F1	F2	F3	ACTUAL	
A1	2	0	1	0	3	66,67%
F1	0	3	0	0	3	100,00%
F2	0	0	3	0	3	100,00%
F3	0	0	0	3	3	100,00%
Predicted	2	3	4	3	12	91,67% AVG. GAIN
%Precision	100,00%	100,00%	75,00%	100,00%	93,75% AVG.PRECISION	91,67% ACCURACY

The values of this table are the averages of the results obtained for each type of fall and activity detected. In the table, we can see that the recognition accuracy of the system proposed is 91, 67%. Since, the % ERROR is small (8,33%) according to[16] the rules can be applied to the classification of new data tuples, and clearly justifies the decision to train the model with historical knowledge. In addition, since the system is closely bound up to healthcare, the precision is very important to reduce the "long lie", which in our system is 93, 75%.

4. Concluding Remarks

The Internet of Things is a new paradigm helping the adult population to improve their quality of life by facilitating a pervasive and more personalized form of care. This study has presented FD-system, an IoT system for fall detection of elderly people based on a Big Data model that uses ML processing techniques based on decision trees. Historical knowledge from an open dataset of falls and ADLs were used for build and training the model, which runs on a Smart IoT Gateway that provides fog computing capabilities. To predict the falls, the FD-system in real time takes as input the acceleration measured in the x, y and z axes coming from the elderly's movements, which were collected with a 3D-axis accelerometer sensor embedded in 6LowPAN based wearable device. The device was placed on the elderlies' waist, and it offers a suitable solution to be used by any elderly person in an indoor environment. The system remotely alerts the healthcare professionals, emergency centers, caregivers and elderly's family members in the case that a fall event occurs using QoS mechanisms. In addition, it guarantees the seamless interoperability by enabling communication paths between all the system's components through the Smart IoT Gateway via protocol conversion functions. This feature enables FD-system to co-exist and be integrated with other applications or external services. Finally, the system generates a new ML model built on cloud, which leveraging the data of the falls detected for perform future predictions. The system performance was evaluated for recognizing three types of falls: fall forward, fall backward and lateral fall while walking caused by a slip. The recognition accuracy, (91, 67 %), precision (93, 75%) and gain (91, 67%) indicate that the proposed system has a high success rate in fall detection.

Work in the near future includes the use of new ML algorithms for the fall detection in order to improve the statistical parameters obtained in this work. We will also integrate this solution with open source platforms focused on ambient assisted living such as UniversAAL in order to provide a holistic and interoperable IoT solution for the AHA of the elderly people.

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