IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 11, 2018, accepted July 11, 2018, date of publication July 31, 2018, date of current version August 28, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2861331

A Novel Monitoring System for Fall Detection in Older People

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This work was supported in part by CORFO - CENS 16CTTS-66390 through the National Center on Health Information Systems, in part by the National Commission for Scientific and Technological Research (CONICYT) through the Program STIC-AMSUD 17STIC-03: ''MONITORing for ehealth," FONDEF ID16I10449 ''Sistema inteligente para la gestión y análisis de la dotación de camas en la red asistencial del sector público'', and in part by MEC80170097 ''Red de colaboración científica entre universidades nacionales e internacionales para la estructuración del doctorado y magister en informática médica en la Universidad de Valparaíso''. The work of V. H. C. De Albuquerque was supported by the Brazilian National Council for Research and Development (CNPq), under Grant 304315/2017-6.

ABSTRACT Each year, more than 30% of people over 65 years-old suffer some fall. Unfortunately, this can generate physical and psychological damage, especially if they live alone and they are unable to get help. In this field, several studies have been performed aiming to alert potential falls of the older people by using different types of sensors and algorithms. In this paper, we present a novel non-invasive monitoring system for fall detection in older people who live alone. Our proposal is using very-low-resolution thermal sensors for classifying a fall and then alerting to the care staff. Also, we analyze the performance of three recurrent neural networks for fall detections: long short-term memory (LSTM), gated recurrent unit, and Bi-LSTM. As many learning algorithms, we have performed a training phase using different test subjects. After several tests, we can observe that the Bi-LSTM approach overcome the others techniques reaching a 93% of accuracy in fall detection. We believe that the bidirectional way of the Bi-LSTM algorithm gives excellent results because the use of their data is influenced by prior and new information, which compares to LSTM and GRU. Information obtained using this system did not compromise the user's privacy, which constitutes an additional advantage of this alternative.

INDEX TERMS Fall detection, older people, artificial neural networks.

I. INTRODUCTION

The effects of fertility decline, along with increased life expectancy, portend the acceleration of global population aging [1]–[3]. A total of 61 million people over the age of 65 in 2004 has been estimated to rise to 2 billion by 2050 [4], [5], which will have profound implications for planning and delivering health and social care [6]. Falls are especially relevant to patients and health systems because approximately one-third of adults older than 65 that live in a community suffer a fall each year [7]–[11]. According to [12], there is an estimation of 3 to 5 falls per 1,000 days of stay in a hospital.

Falls older people often result in more serious injuries than falls associated with younger patients, and the associated costs with this are very high [13]. Moreover, the mortality rate of older people who have suffered some sort of fall is significantly higher than those who have not suffered any falls, with an odds ratio (OR) of 5.11 (CI 95% 1.84 - 14.17, $p = 0.002$) [14]–[16].

Recently, numerous studies in the area of fall detection have arisen in an attempt to solve this problem [17]–[19]. In terms of sensor technology developed up to date, each proposed system can be classified into: a wearable-based system, a camera-based system, and an ambience device [20].

The focus of wearable devices consists in the user carrying some type of device with embedded sensors that detect changes in posture and body movement in order to use classifiers or some type of AI that will detect falls. Thanks to

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the implementation of these types of systems, it has been possible to develop fairly durable devices with high precision. Wang *et al.* [21] propose the use of a wearable device with an estimated battery life of 664.9 days and with high sensitivity and specificity in its test dataset (93% and 87.3%, respectively). Althongh the performance of these devices is promising, they have the disadvantage of being intrusive as well as the probability that the user does not carry it, either by choice or forgetfulness, therefore countermanding its main goal [22].

Devices based on cameras have multiple advantages, among them the ability to detect multiple events simultaneously, not being intrusive systems, and possessing high precision in fall detection. For example, [19], formulates the use of video cameras to detect falls through the implementation of Exponentially Weighted Moving Average based on Support Vector Machines (MEWMA-SVM), which achieved high precision in fall detection (97.2%), which contrasted with other algorithms. However, in spite of the multiple advantages the use of cameras provides to detection of events such as falls, their implementation in homes of older people is complicated due to the invasion of privacy that is implicit in their use. Although the system only processes information locally and does not rebuild images for its operation, users may still not accept it, considering it an intrusion to their privacy.

The other type of device involving fall detection consists on ambient devices. These systems can use one or multiple non-intrusive sensors to measure variables within the environment in which the user is interacting. Some examples include the detection of pressure on the floor, infrared temperature, sound, electromagnetic waves, etc. Based on these sensors and the application of intelligent algorithms, it is possible to detect, with high precision, when a person suffers a fall. For example, in [23], a proposal is made for the use of low-cost infrared sensor arrays to detect falls, along with a performance demonstration of known artificial intelligence algorithms used with this sensor.Using MLP and GRU-ATT algorithms, the investigators reported a 97% precision to detect falls. Although the use of these sensors is generally limited to controlled environments, their use is more accepted by users compared to the use of video cameras [22].

In this study, we present the development of a fall-detection system applied to very low-resolution infrared sensors for classifying potential falls suffered by older people. This system was developed to alert caretakers that a fall has occured. Sensors of the proposed system are equipped with an array of 16×2 pixels, which assures that the privacy of users is not infringed while the device is being used. The system is designed to be employed in homes of older people that live alone. To process the data from the sensors, three models of recurrent neural networks (RNN) were implemented, analyzing temporal sequences to compare results. These are LSTM, GRU, and Bi-LSTM; we have used these RNNs because they have been highly used for classification problems [24]–[26]. A training phase for our proposed approaches was conducted prior the initiation of the formal classification phase.

After performing several tests with people, we have achieved a 93% of accuracy in the fall detection using the Bi-LSTM approach. These results are promising, not only for their high accuracy, but also because this system does not compromise privacy in any way.

The article is organized as follows: Section II summarizes work already developed in this area of study and the contribution of each one of these works. Sections III and IV detail the used methodology, such as the implemented system and the algorithms used in the processing of information, the test environment, sensor characterization, and used dataset. Section V shows the obtained results in the classification of falls along with a brief discussion in Section VI. Finally, conclusions and future work are presented in Section VII.

II. RELATED WORK AND CONTRIBUTION

The utilization of infrared sensor arrays in fall detection has been previously addressed in other publications, in which architectures and proposed algorithms have been designed with varied results in their precision. The use of low-resolution thermal sensors is a viable alternative for this purpose, given that they are cost-effective, non-intrusive, and can yield distinct types of information such as position, velocity, acceleration, and human body temperature in a controlled environment [22], [23], [27], [28].

Sixsmith and Johnson [22] performed one of the first studies using low-resolution infrared sensor arrays (16×16 pixels). His system, which was trained with 108 scenarios and 10,000 training vectors, uses MLP neural networks to classify falls. Furthermore, the system is equipped with a module to send alerts via GSM. Although his results were not encouraging due to his training set, it is explained that the motivation behind using these sensors is for their excellent acceptance by users in respect to privacy (in comparison to camera-based systems).

Taniguchi *et al.* [28] utilizes two low-resolution sensor arrays (16×16 pixels), one located on the wall and the other one on the ceiling. The system algorithm consists of estimating body posture and detecting a fall by means of changes in posture over time. The diagnostic accuracy of the system in its worst scenarios were around 72.7%. His work concludes that this system detects falls successfully and that it could be considered for implementation in monitoring.

One of the more recent studies that focuses on infrared sensors is that of Fan *et al.* [23]. The study evaluates the application of various Deep Learning methods, including LSTM and GRU, applied to the use of low-resolution infrared sensor arrays (8×8 pixels). The results are very promising, achieving in the worst case, a precision of 75% for the GRU-ATT algorithm and 85% for LSTM. Recently, the use of recurrent neural networks has produced satisfactory results in diverse studies thanks to their ability to consider temporal data sequences. Their use has been applied in various areas, such as voice recognition, image processing, and signal processing, etc. [29].

The principal contribution of our work, with respect to the state of the art, is the implementation of recurrent neural networks with a convolutional layer applied to infrared sensors (16 × 2 pixels) for fall detection. Due to growing computational resources, recurrent neural networks (RNNs) (which have been around for decades, but their full potential has only recently begun to become widely recognized in forms such as convolutional neural networks (CNNs)) have recently generated a significant development in the domain of deep learning [30]. Our work employs four 1 × 8 pixels sensors with the aim of reducing the amount of information processed by the neural network, thus optimizing resources and, in addition, increasing the user's perception of privacy. The sensors are located on two horizontal planes: two sensors at 1 meter from the floor, and the other two at 10 cm from the floor. Both horizontal planes cover approximately 124° of the surrounding scenario with a resolution of 16 × 1 pixels.

Regarding the algorithm proposed for fall detection, which corresponds to Bi-LSTM, it considers a temporal data sequence in order to obtain a result; for this reason, its application in the detection of falls is of interest given that a fall cannot be solely determined by one temporary sample, but should also consider prior samples into consideration [28]. F In addition, other recurrent neural network approaches (LSTM and GRU) are evaluated as well in order to provide comparative data of the different algorithms. Every algorithm was implemented with a convolutional input layer, which was used to extract hierarchical characteristics from input signals. Algorithms were tested using a low-cost single board computer to assess the feasibility of its implementation in future smart homes.

III. METHODOLOGY

In this study, a non-intrusive fall detection system for controlled enviroments was implemented. The system does not use invasive components, such as cameras or microphones and is aimed at improving care for the elderly (see Figure 1).

Figure 1 shows the high-level architecture of the proposed system. The system measures the ambient temperature through low-resolution thermal sensors. These sensors are responsible for detecting the body-heat of the user without having to be in contact with the older people (maximum distance of 4 meters). The data is stored in a local database and transmitted to a server for further analysis. In parallel, through the implementation of AI algorithms, it is possible to classify if there has been a fall with 93% accuracy. If the fall occurs, the system sends emergency alerts to their families and the health service staff.

IV. MATERIALS & METHODS

The tests and implementation of the system were approved by the Comité de Bioética de la Universidad de Valparaíso (Universidad de Valparaíso Bioethics Committee, code CB086-15). In addition, each participant voluntarily expressed his interest to participate in the research by the approval and signature of an informed consent. In order to detect falls, passive infrared sensors of continuous measurement were used due to the fact that they constantly record the temperature generated by an object, unlike other sensors such as Passive Infrared Motion Sensor (PIR), which only reacts to changes in infrared radiation.

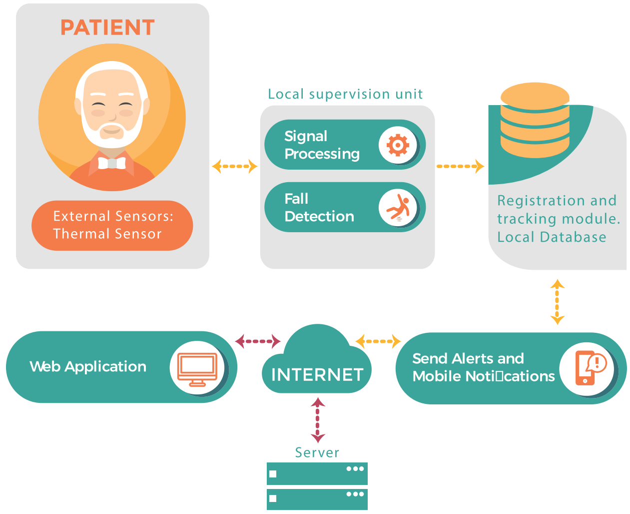

FIGURE 1. System architecture.

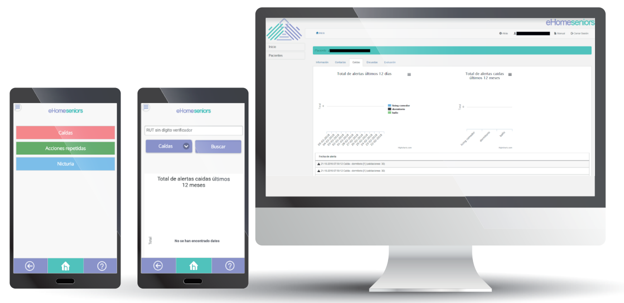

FIGURE 2. Web and mobile platforms.

A. SYSTEM ARCHITECTURE

The fall-detection device, detailed in the following sections, sends alerts using 3G networks to the server, which then stores the information in databases developed in PostgreSQL, and then sends alerts to a web platform and a mobile device developed for this purpose. The web platform was developed in PHP with the Laravel framework; its functions include receiving alerts and administrating formulas with clinical information about the older adult. Also, the web platform allows managing data of the monitored patients (add, modify delete). Additionality, the web platform allows to register and monitor survey results, medical history and event frequency.

The mobile platform was developed using the Cordova 6.4 framework and receives alerts from the server and shows information about the older adult. Figure 2 shows interfaces of web and mobile developed platforms.

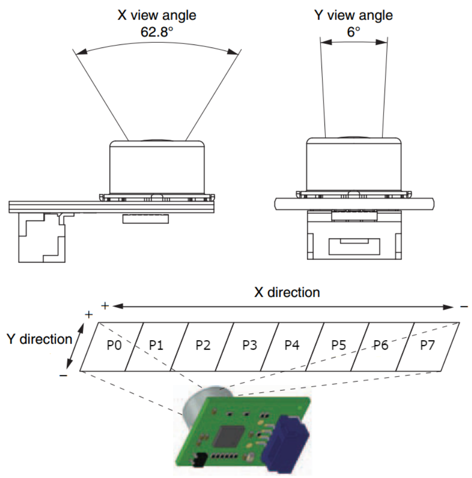

FIGURE 3. Field of view OMRON D6T-8L-06 sensor.

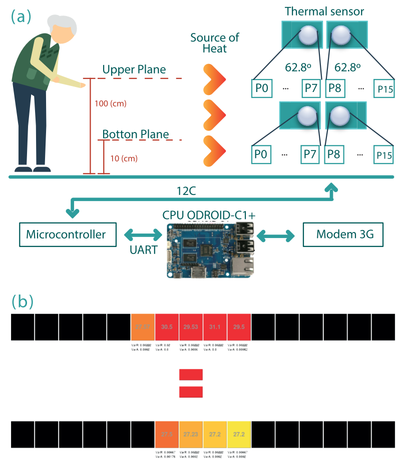

FIGURE 4. Coverage angle and measurement planes. (a) Proposed system. (b) Pixels and program for processing data.

B. HARDWARE IMPLEMENTED

The sensor used was an OMRON D6T-8L-06, which is made up of a cap with a silicon lens, MEMS thermopile sensor chips, a dedicated analog circuit, and a logic circuit for converting to a digital temperature value on a single board through an I2C interface with a 100kHz clock. The silicon lens collects radiated heat with an object onto the thermopile sensor in the module, generating an electromotive force, which is used to calculate the temperature through an analog circuit and which is consulted via I2C protocol. This sensor has an array chip of 8 channels (1×8 pixels), which gives a view angle of $62.8° \times 6°$, as depicted in Figure 3.

The computer used to capture, process data, and send alerts was a powerful, low-cost, single-board ODROID-C1+ computer. This mini PC has a 1.5Ghz quad-core processor, MaliTM-450 MP2 GPU, 1Gbyte DDR3 SDRAM, 40pin GPIO, and runs Ubuntu 16.04. In order to operate this system, it was necessary to connect four OMRON sensors to an ATMEGA328P microcontroller, which reads sensor data and sends it to the ODROID-C1+ via UART interface with a baud rate of 115,200 and a sample rate of 5[Hz]. Figure 4(a) shows an schematic diagram of the system. The cost of this system amounts to US$150.

The system is designed to be placed in a corner of a room, measuring the heat received in two horizontal planes: one plane located at one meter away from floor level (Upper Plane) and another plane about 10[cm] above the floor (Bottom Plane) (see 4). Due to the fact that each sensor is capable of covering 62.8°, it is necessary to install 2 sensors to avoid leaving any blind areas, increasing coverage to 125.6°. Thus, it has 16 resolution pixels for both planes as shown in Figure 4(b)).

C. ALGORITHMS

The focus of this article refers to the utilization of Deep Learning to detect falls, using the information from each pixel in the temperature sensors as a source. Given that the action of falling involves a dynamic process that varies over time, temporal data sequences are taken into account in order to classify them, implementing recurrent neural networks. The architecture used is composed of four layers, which are shown in Figures 8 and 9, and whose details are described as follows:

- Convolutional layer: Receives the input vector in order to extract hierarchical characteristics that improve classification.
- MaxPooling layer: Reduces the quantity of hierarchical characteristics, leaving the most important ones.
- RNN layers: Consists of the implementation of two RNN layers of type LSTM, GRU, or Bi-LSTM.
- Dense layer: Consists of a perceptron-type neural network used to obtain an ouput between 0 and 1 through the function of sigmoid activation, which would indicate whether a fall occurs or not.

1) CONVOLUTIONAL LAYER

A 1-dimensional convolutional layer with a 3 element linear kernel is implemented with the objective of extracting hierarchical characteristics from the pixels captured by each sensor (vector of 32 elements). By using this approach, the next recurrent layer extracts more precise information that will be used to establish the essential elements that can be processed in a temporal format. Additionally, this helps to reduce computational expenditure that is made in the recurrent layer. The convolutional layer is implemented with the ReLU activation function due to its characteristics that allow it to reduce the effects of vanishing gradient, achieving faster learning [31].

2) MAXPOOLING LAYER

This layer is formed by a 1D MaxPooling with a 2-pool size and has the ability to reduce the number of characteristics encountered, leaving only the ones of interest for the network and therefore obtaining a better capacity for generalization [32]. It is important to note that the algorithm should be implemented in a single-board computer so as to reduce costs

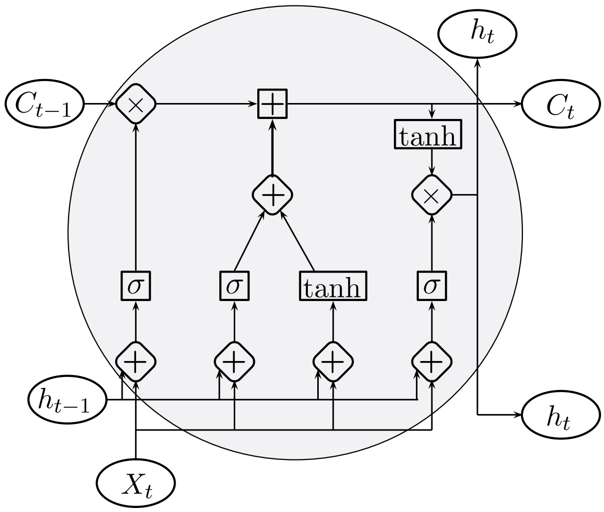

FIGURE 5. Schematic LSTM unit.

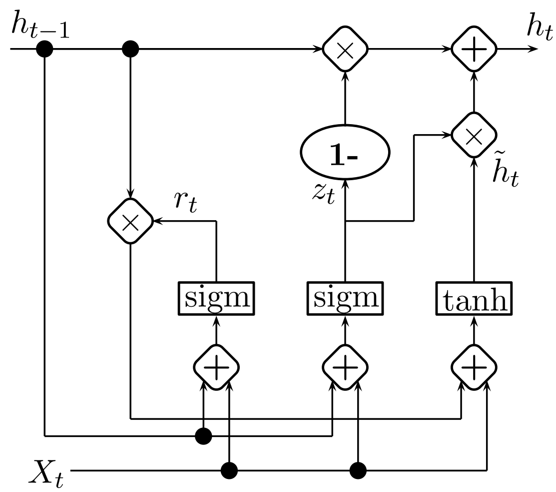

FIGURE 6. Schematic GRU unit.

of implementation, and therefore a reduction of parameters is necessary in order to improve performance.

3) LONG SHORT-TERM MEMORY (LSTM) MODEL DESCRIPTION

This recurrent neural network was introduced and designed by Hochreiter and Schmedhuber (1997) [33] to handle temporal data sequences and also to be able to confront the exploding and vanishing gradient problems, which is a recurring problem with traditional RNNs. This type of neural network is equipped with a memory cell, which can store values that are recorded over time in correspondence with past information. The memory cell can be controlled in the following manner: the forget gate is tasked with storing or deleting information, the input gate is tasked with adding new information and the output gate controls the output flow. LSTM network generates two states at every single time-step: a cell state that is transferred into the next time-step and a hidden state that is the output vector of the time-step [34]. Figure 5 shows a schematic of the LSTM recurrent neural network.

The model of this neural network can be described by the following equations:

$$f_t = \sigma\left(W_t \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_i] + b_i\right) \tag{2}$$
$$C_t' = tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{3}$$
$$C_t = f_t * C_{t-1} + i_t * C_t' \tag{4}$$
$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{5}$$
$$h_t = o_t * tanh\left(C_t\right)) \tag{6}$$

Where * indicates element-wise multiplication and σ indicates element-wise sigmoid function. f_t, i_t, and o_t correspond to forget gate, input gate, and output gate, respectively. b_f, b_i, b_c, and b_o correspond to the bias units of forget gate, input gate, output gate, and memory cell, respectively. c_t is the state of the memory cell; h_t is the output vector, and W_f, W_i, W_c, and W_o are trained weight matrices. While LSTMs possess the ability to learn temporal dependencies in sequences, they have difficulty with long term dependencies in long sequences [24].

4) GATED RECURRENT UNIT (GRU) MODEL DESCRIPTION

This recurrent neural network model is very similar to LSTM, since it addresses the vanishing gradient problem and its internal structure is more simple and rapid to train. However, instead of being equipped with three control gates, it only has 2: reset gate and update; this means that less computations are necessary to update its hidden state. This model was proposed in [26], and the corresponding schematic is shown in Figure 6.

The equations that define this recurrent neural network model are given by:

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t] + b_r\right) \tag{7}$$
$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t] + b_z\right) \tag{8}$$
$$\bar{h}_t = tanh\left(W_h \cdot [r_t \cdot h_{t-1}, x_t] + b_h\right) \tag{9}$$
$$h_t = z_t \cdot h_{t-1} + (1 - z_t) \cdot \bar{h}_t \tag{10}$$

Where z_t and r_t correspond to update gate and reset gate, respectively, while $\bar{h}_t$ is a candidate for a new state and h_t corresponds to the activation of the state. x_t corresponds to input in time t. W_z, W_r, and W_h are trained weight matrices, while the bias vectors are represented by b_r, b_z, and b_h.

BIDIRECTIONAL LSTM (BI-LSTM) MODEL DESCRIPTION

This type of recurrent neural network is designed to work with temporary data sequences, but, unlike LSTM, where elements are influenced only by past information, Bi-LSTM considers both past and future elements. It is equipped with two parallel layers called backward and forward, which can pass information in the same manner that LSTM does, but in both directions [25]. A schematic of this model is shown in Figure 7.

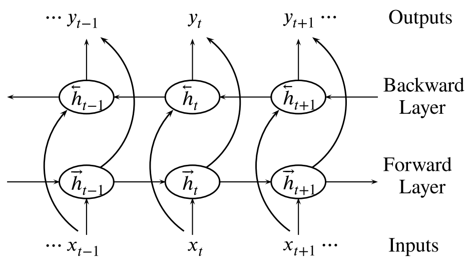

FIGURE 7. Bidirectional recurrent neural network.

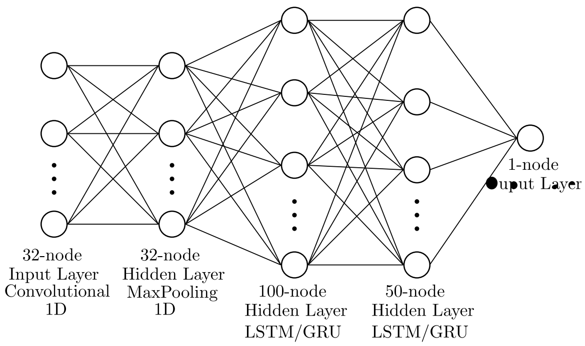

FIGURE 8. Implemented architecture for LSTM and GRU units.

This bidirectional LSTM network is implemented through the following equations:

$$\vec{h}_t = LSTM\left(x_t, \vec{h}_{t-1}; \vec{W}\right) \tag{11}$$

$$\overleftarrow{h}_t = LSTM\left(x_t, \overleftarrow{h}_{t-1}; \overleftarrow{W}\right) \tag{12}$$

$$y_t = \left[\vec{h}, \overleftarrow{h}\right] \tag{13}$$

Where $\vec{h}_t$, $\overleftarrow{h}_t$, $\vec{W}$ and $\overleftarrow{W}$ are hidden states and weight matrices of the forward and backward layers, respectively. Output y_t is determined by the concatenation of $\vec{h}_t$ with $\overleftarrow{h}_t$.

5) RECURRENT NEURAL NETWORK ARCHITECTURE

The architecture implemented consists on a hybrid model that utilizes a 1D convolutional layer with a 3-element kernel, tasked with highlighting special relevant characteristics through trained filters. Then, a MaxPooling layer reduces the number of characteristics, leaving only the most important ones, and therefore mitigating the effects of changes in scale and orientation over different training data. This helps to reduce the effects of overfitting and also lessens computational cost. Two recurrent layers are then implemented for both the LSTM model and the GRU model, whose outputs pass through a dense layer with a sigmoid activation function. Figure 8 shows the architecture described for both LSTM and GRU models.

The architecture implemented for the neural network Bi-LSTM is similar to the previous one, the difference being that the recurrent layer implemented is bidirectional. This allows it to recognize temporal sequences, taking into account forward and backward data. Figure 9 shows the architecture implemented for Bi-LSTM.

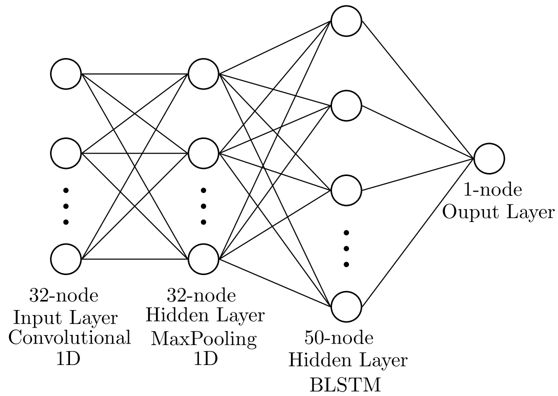

FIGURE 9. Implemented architecture for Bi-LSTM unit.

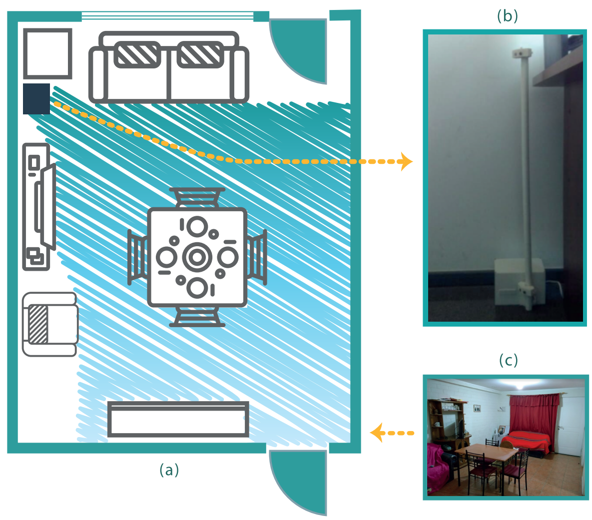

FIGURE 10. Testing environment. (a) System coverage area. (b) Fall system design. (c) Testing room.

V. EXPERIMENTS

TESTING ENVIRONMENT

The system was placed in a corner of a 4x5 meter room and tested.

Figure 10 (a) shows a schematic of the room where the fall sensor is represented by a blue box and the data capture area is represented by green color. The ambient temperature during the experiment varied from 16[°C] to 20[°C]. The whole system was mounted on a structure especially designed for this purpose with a 3D printer (see Figure 10 (b)). Finally, Figure 10 (c) shows the room where the tests were made.

A. TESTING TEMPERATURE SENSOR

The temperatures obtained by a pixel of the sensor when facing a person at chest height with different types of clothing and 4 different distances (1, 2, 3, and 4 meters) were analyzed. For every distance and type of clothing, 30 temperature measurements were taken over a 30-second period. This experiment was carried out with a 27-year old male volunteer of 1.7 m (5.57 ft.) who weighted 64 [kg] (141.1 lb.). Measurements with a bare torso, wearing a T-shirt and a

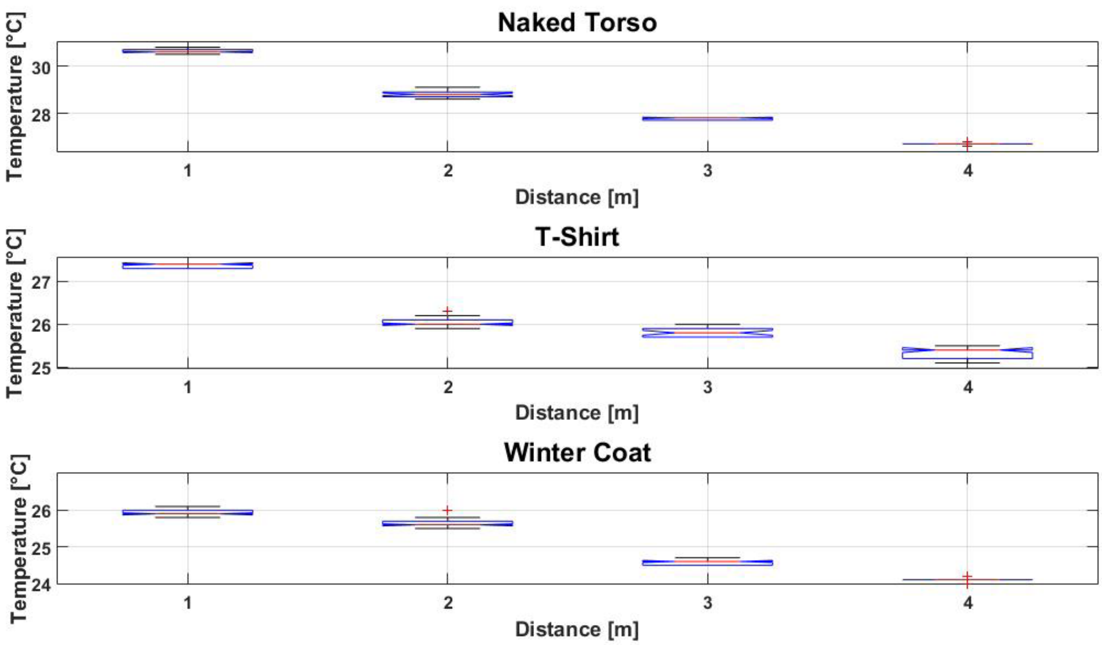

FIGURE 11. Changes in the temperature detected by the pixel being in the presence of a person with different clothes and at different distances from the sensor.

winter jacket were obtained. Figure 11 shows the changes in the temperature detected by the pixel being in the presence of a person with different clothes and at different distances from the sensor.

In Figure 11, it can be seen that the temperature measurement is affected by the distance of the person from the sensor, since the area occupied by the person in the field of vision of the sensor becomes smaller, increasing the distance; in this way, the ambient temperature tends to prevail.

To check the temperature variation ranges within the test environment, data was obtained from the sensors at a sampling rate of 1Hz for a 24-hour period. The data obtained for each pixel in each plane are shown in Figure 12. Each pixel delivers temperature values consistent with those measured by a conventional mercury thermometer and the dispersion of the temperature values per pixel vary in a small range, negligible in comparison to the presence of a person as seen in Figure 11.

Given a set of temperature values of upper and bottom planes, $P_U = \{P_{U_0}, P_{U_1}, \ldots, P_{U_{N\text{-}1}}\}$ and $P_B = \{P_{B_0}, P_{B_1}, \ldots, P_{B_{N\text{-}1}}\}$ respectively, with $N = 16$. Figure 13 shows the information obtained from the temperature sensor for the last 8 pixels (P_{U_8} to $P_{U_{15}}$ for the upper plane and P_{B_8} to $P_{B_{15}}$ for the lower plane) when observing a person's behaviour. It can be seen in the first few seconds that the person walked at a distance of 2 meters from the sensor and then at 9.5 [s] suffers a lateral fall to the left and, as a consequence, the pixels in the upper plane only detect the ambient temperature in their monitored field and the pixels in the lower plane detect a higher temperature as the person is lying on the floor.

TABLE 1. Characteristics of participants.

Male/Female	2/2
Age	25-37
Weight (Kg)	47-79
Height (cm)	147-182

B. DATA SET EXTRACTION

The dataset was obtained through four test subjects whose ages are in the range of 25 to 37 years; this is due to the fact that real falls in older people cannot be simulated due to the risk of injury. The characteristics of the participants are shown in Table 1.

The ways in which a person can suffer a fall vary, which implies limiting a certain number of situations representative of this event for the evaluation of the system. Usually a forward fall begins with loss of balance, causing the person to advance a couple of steps to recover by stretching out arms and possibly falling onto the knees. Another scenario is that the person, when falling backward, sits down to reduce the impact of the fall. The scenarios that were be evaluated for fall detection, as well as those that represent daily-life movements, are shown in Table 2 and Table 3. Participants simulated each of the aforementioned scenarios (in Table 2 and Table 3), and a total of 208 iterations were obtained comprising 96 falls and 112 daily-life movements.

C. TRAINING PROCCESS

During the training process, 60 time sequences of data were used from the sensors, where each element of these sequences corresponds to 32 temperature values taken in

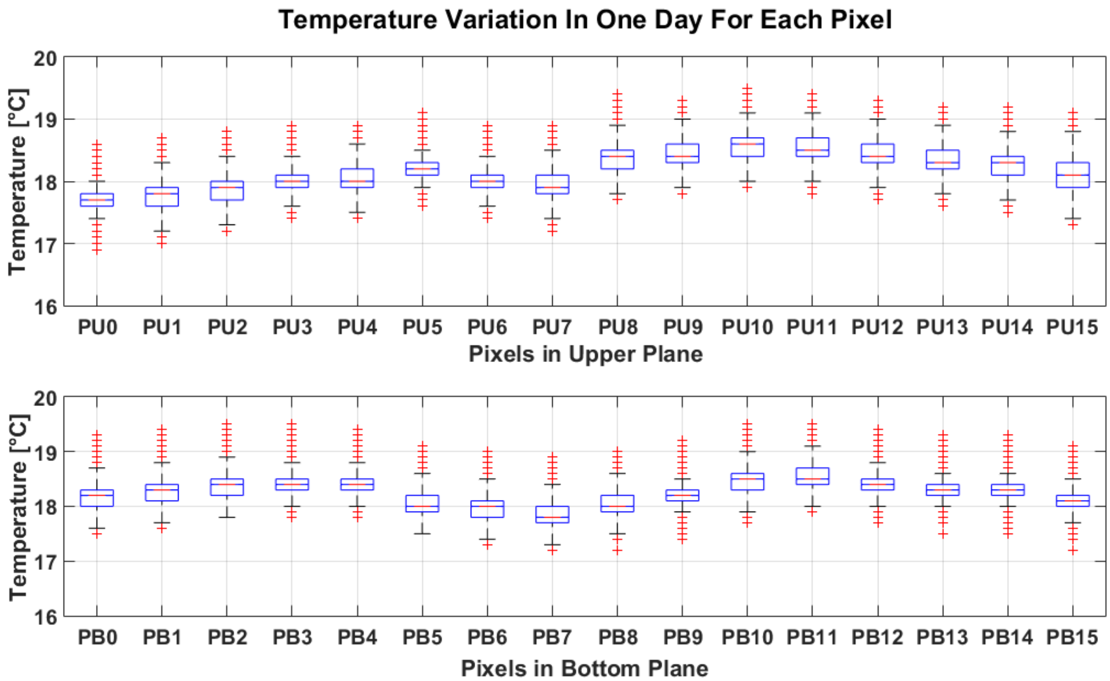

FIGURE 12. Temperature variation in one day for each pixel.

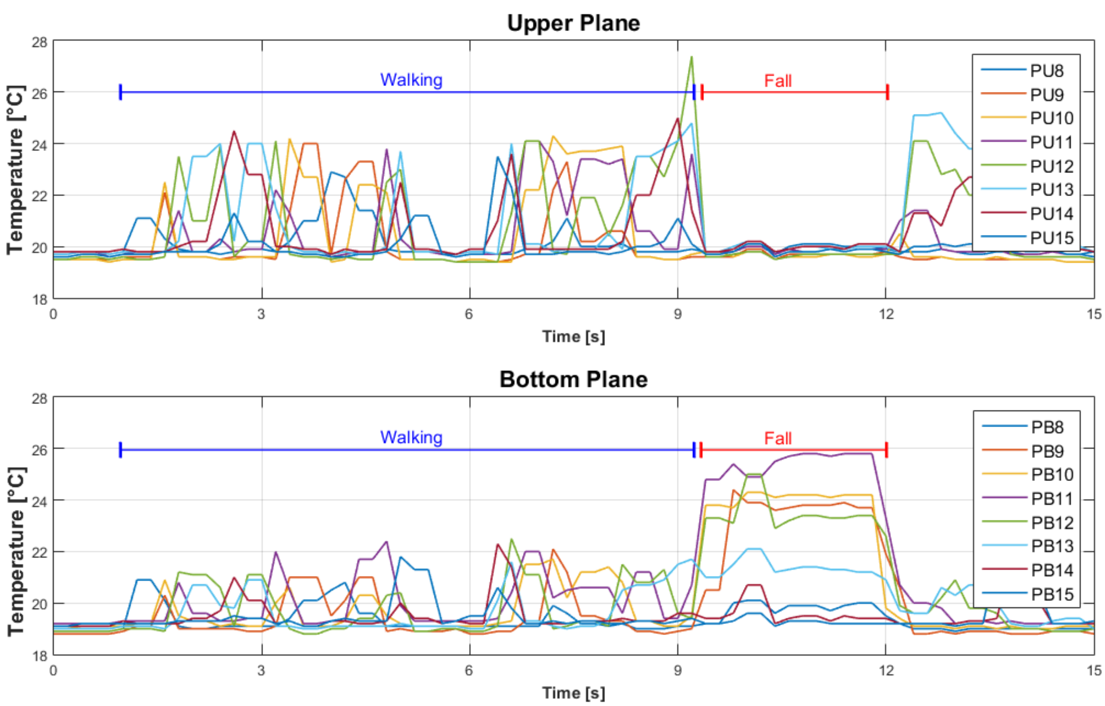

FIGURE 13. Temperature detected in 8 pixels in response to a person walking and then falling at 9.5[s].

each measurement. The sequences were entered in batches of 4 for each epoch.

With the objective of fixing the optimal number of epochs in each case, a validation set equivalent to 20% of the training set was used in order to apply early stopping. Both database and the implemented models can be revised in [35].

In order to avoid overfitting, a dropout regularization procedure was implmemented in every model. Layers of probability of 0.2 were used [36], which implies that connections were temporarily eliminated in each iteration prior to calculating averages of each subnet's results. Furthermore, batch normalization was used as a way to accelerate the training

TABLE 2. Scenarios of evaluation of falls.

Category	Name	Fall Samples
Backward fall (both legs straight or with knee flexion)	Ending lying	8
	Ending in lateral position	8
	Ending sitting	8
Forward fall	With forward arm protection	8
	Ending lying flat	8
	With rotation, ending in lateral right position	8
	With rotation, ending in lateral left position	8
	Ending on the knees	8
Lateral fall to right	Ending lying flat	8
	Ending lying while sitting	8
Lateral fall to left	Ending lying flat	8
	Ending lying while sitting	8

TABLE 3. Scenarios of evaluation of daily-life movements.

Category	Name	Daily-life movements samples
Walk	Walking slowly and quickly	16
	Stumble while walking	8
Jogging	Jogging slowly and quickly	16
Sit down	Quickly sit in a chair, wait a moment, and stand up quickly	16
	Slowly sit in a chair, wait a moment, and stand up quickly	16
	Sitting a moment, trying to get up, and collapsing into a chair	8
Crouch down	Crouch down bending the knees, wait a moment and then getting up	8
	Crouch down without bending the knees, wait a moment and then getting up	8
Jump	Gently jump without falling	8
Rotate	Rotate 180° in front of sensor	8

process [37], making the model conform to the specific distribution of each mini batch.

VI. RESULTS AND DISCUSSION

The performance of systems was evaluated by the calculation of accuracy, sensitivity, and specificity. To carry out the calculation, we labelled the true positives as *TP*, the false positives as *FP*, the true negatives as *TN*, and the false negatives as *FN*. The calculations of accuracy, sensitivity, and specificity are obtained by means of the expressions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{15}$$

$$Specificity = \frac{TN}{TN + FP} \tag{16}$$

Table 4 summarizes the results obtained with each of the implemented models, trained with the published datasets in [30]:

From the architectures tested, satisfactory results were obtained for each of the models. However, it is pertinent to highlight the differences in detection capacity, robustness against possible false positives, and performance.

Detection capacity gives an account of how well the system recognizes a fall and represents the main objective of this work, since the physical integrity of a person can depend on this. The model that best served in this aspect was Bi-LSTM, thanks to its ability to analyze the temporal sequences in both directions, achieving 93% sensitivity in contrast to LSTM and GRU, which achieved 89% and 85%, respectively. On the other hand, the specificity of each model reached 93% for Bi-LSTM, 93% for LSTM, and 89% for GRU. This is because GRU has fewer gates than the other two models, being able to consider a lesser number of determining aspects. By implementing each of the models in the ODROID C1 single-board computer, the responsing time were 38 ms for LSTM, 35 ms for GRU and 45 ms for Bi-LSTM, which is negligible for the developed application. However, it is expected that the GRU algorithm has a lower response time by having fewer gates and requiring less computing capacity.

In our dataset, Bi-LSTM algorithms showed the best combination of sensitivity and specificity which reached 93% in both cases. The least successful estimates were obtained with GRU analysis strategies. In order to facilitate comparisons between these different approaches, 95% confidence intervals were calculated for each of the diagnostic accuracy estimates. As shown in Table 4, no evidence of a statistically significant contrast was observed amongst the aforementioned analysis strategies.

In its current version, this system is designed to be used in controlled homes of elderly people who live alone, since the presence of more people or pets might affect system performance. The tests performed showed good diagnostic accuracy in the detection of falls, however there was a lower number of false positives due to the increase of temperature in objects. This might be relevant whenever these elements come into contacto with the human body. In this way, the presence of objects with temperatures higher than room temperature, such as heaters, can generate false positives that affect system performance.

Improving the training of the neural networks implemented, together with testing other architectures, can improve

TABLE 4. Results of the implemented algorithms.

	Accuracy (95%CI)	Sensitivity (95%CI)	Specificity (95%CI)
LSTM	91% (86.1% - 94.4%)	89% (80.4% - 94.1%)	93% (86.4% - 96.9%)
GRU	87.5% (82.2% - 91.7%)	85% (76.7% - 91.8%)	89% (82.0% - 94.3%)
Bi-LSTM	93% (88.4% - 95.9%)	93% (85.5% - 97.0%)	93% (86.4% - 96.9%)

accuracy in the detection of falls. Furthermore, the location of the sensors is essential in obtaining accurate results, because the presence of obstacles such as furniture can create blind spots where the person could suffer a fall and not be detected. Despite these limitations, if the conditions are optimal, this system can deliver accurate results through an easy system implementation in households.

VII. CONCLUSIONS AND FUTURE WORK

The number of older people living alone worldwide increases daily. In Chile, the elderly represent roughly 330.000 persons, which represents more than 2% of the population [38]. A significant proportion of these persons lives alone, which makes obtaining help in the case of a fall much more difficult [8]–[11]. In this work, we propose a non-intrusive fall-detection system for controlled environments that does not compromise the privacy of the user based. This developent is based on thermal sensor array for older people living alone. Three algorithms of recurrent neural networks have been implemented: Bi-LSTM, LSTM, and GRU, showing a good performance on each one of these when detecting falls, highlighting among them the model Bi-LSTM. Although the proposed system has certain disadvantages, such as being prone to uncertainty on ambient temperature and the presence of objects in the area of coverage, its installation in controlled households represents an important contribution to their care.This system shows promise as a device that might allow the provision of timely assistance should a fall occur, and could also lower costs associated with these accidents. As future works, we plan to test similar thermal sensors in different locations to evaluate their results and to perform tests in less-controlled clinical environments to further validate this system.

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