Deep Learning with network of Wearable sensors for preventing the Risk of Falls for Older People

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Abstract. Activity recognition (AR) systems for older adults are common in residential health care including hospitals or nursing homes; therefore, numerous solutions and studies presented to improve the performance of the AR systems. Yet, delivering sufficiently robust AR systems from sensor data recorded is a challenging task. AR in a smart environment utilizes large amounts of sensor data to derive effective features from the data to track the activity daily living. This paper maximizes the performance of AR system from using the convolutional neural network (CNN). Here, it analyzes signals from the network sensors distributed in different places in two clinical rooms at the Elizabeth hospital, such as W2ISP and RFID sensors. The proposed approach recognized the daily activities that consider a key to falling cases for older adults at a hospital or a nursing health house. A deep activity CNNets is used to train the effective features of daily activities sensors data then used for recognizing the highest falling risk activities in testing data. This approach used existing data of fourteen healthy older volunteers (ten females and four males) and then compared to other proposed approaches that used the same dataset. The experimental results show that this approach is superior to others. It achieved (96.37±3.63%) in the first clinic room and (98.37±1.63%) in the second clinic room. As the result, this experiment concludes that deep learning methodology is effectively assessing fall risk based on wearable sensors.

Keywords: Activity Recognition, CNNets, RFID sensor, Deep Learning, Convolutional neural network

1 Introduction

Due to Activity recognition (AR) system has become required for healthcare either at a hospital or nursing home. In general, AR is still a challenging problem for many researchers around the world, and they are looking for a way to keep the elder people’s lives safely. Most smart devices have embedded sensors to identify and recognize body’s movements. As a result, these devices are calculating the movement percentage for all type of users at the end of the day [1].
This study used a special type of sensor to monitor activity recognition system and detect human's movements for healthcare. In this experiment, many of RFID sensors used in two clinic rooms at the hospital to collect data from health elder people. The aim is to identify the worst activities that might cause danger of elder human's life. There are many types of body daily activities such that ambulation types of activities e.g. sitting, standing, lying, walking upstairs, walking downstairs and walking of classifications [2] and recognize the activities according to those categories. The study focus on four daily activities which are considering a key point that can discover a dangers case to the older people. These are sitting on bed, lying, ambulating and sitting on chair.

The healthcare system has been improved by new technological innovations such as Smart Item Technology, (IoT), and cloud computing and extended service provision beyond the hospital facilities by using (WSN) and radio frequency identification devices (RFID) sensors. With this type of services, either doctors or elder people enable to treat remotely and do normal daily routines, occupations, and activities while receiving appropriate, timely, and high-quality ubiquitous healthcare services [3].

Due to the success of deep learning algorithms, many huge companies have used in their studies such as Google, Apple, Facebook, Netflix, Microsoft and IBM [4]. Moreover, it has used to detect and recognize many other complicated problems like the Alzheimer’s disease [5], Handwritten Arabic Numeral Recognition [6], etc. Therefore, a deep learning methodology is a technique for machine learning that discovers and learns the features from the processing of multiple layers of input dataset.

2 RELATED WORKS

There are many uses of smart technologies that help and simplify people’s life to monitor their activities such as cloud computing and sensors. These technologies enable researchers who are interested in the healthcare field to develop a new system to serve the patients from elder people either at a medical center or a nursing house. Due to this revolution progress in this filed many challenges came up and needed to be solved and cleaned such as activity recognition and detection. Many researches were done and submitted in this field to support and develop this type of service to make the healthy life more flexible, easier and controlled:

The past years researchers cleared that one of the issues in the field of nursery houses and nursery hospitals is the activity recognition and health monitoring for healthy and unhealthy elders. According to the indications of the United Nations, by 2050 there are 64 countries around the world would have in their population more than 30% of elders [7]. Falls were said to be one of the action problems because it expected to be increased so that most of the recommendations in hospitals is to prevent falls [8]. In addition, [9] determined that falls were a direct cause of 26 patient death, many reports of physical injuries, 530 hip fractures and a 1000 other types of fractures, the psychological consequences such as losing confident, falling fear, anxiety, depression, and a continuous lake in individuals health. Due to the world wide aging expectations [10], [11], [12] and [13] which based on the increasing in the individuals life and the decreasing in the birth ratio. Researchers in this field studied and implemented many applications, theories and algorithms to enhance people’s lives and afford the sense of security by remotely monitoring their health and analyzing behaviors which leads to enhance elders living. However, fall rates still unacceptable and high.

Sensors were one of the official ways that had been used to collect and monitor activities. Using a sensor in a smartphone is one way to detect a falling case for elder and prevent any injury accident [14]. Recently, the sensors patients worn provided a better monitoring for different patient simultaneously [15]. RFID sensors, the battery less sensors that appeared for the first time in [16] which used two types of technology: the lightweight radio frequency identification composed with the integrated kinematic with healthy-young volunteers. The paper [17] Found that those type of sensors where more acceptable by
elders. Researchers did not stop on using one sensor only but in some cases they expand it to use multiple sensors to monitor patients and to collect accurate rich data [13], [18], [19]. However, the data contained unwanted delay according to the machine learning classification algorithms although they did not investigate bed-egress recognition [18], [19]. Decision trees, ensemble, logistic regression, Deep Nets and other machine learning algorithms used to detect emergency cases for falling elderly [20], [21].

3 METHODOLOGY

3.1. Wearable sensor technology

The wearable sensor that utilized and developed in [17], [22], [23], [24] and [25] consists of W2ISP which is a passive enable RFID sensor known as Wireless Identification and Sensing Platform. It works based on WISP and includes (ADXL330) which is a triaxial accelerometer sensor, and it has a microprocessor of type (MSP430F2132) with a silver fabric that will be easy to isolate from a patient [26]. The RFID's structure consists of a UHF-based on RFID reader (IPJ-REV-R420-GX11M running in the frequency band 920-926 MHz) and circularly polarized antennas (Laird S9028PCLJ) [27]. It is a small device, lightweight and self-charging battery which can be easily used to monitor the elder. The W2ISP’s battery works based on the energy that happened of the electromagnetic field that illuminated in [27]. The RFID used the air interface protocol (ISO 18000-6C) [28] and [29] to communicate with the W2ISP. The RFID is utilized to activate and collect data from W2ISP where a single sensor of RFID can connect with multiple antennas of W2ISP using an electronic identifier attached sensor data.

![Figure 1: Illustration of Monitoring Activity analysis framework.](image)

Two sources of information are available from this setting (Figure1). The first one is the triaxial accelerometer including in W2ISP measures the acceleration of motion that happens from a participant and the gravitational element along the axes of acceleration: frontal (af), vertical (av) and lateral (al) (Figure 2). The second is the RFID reader provides signal activation and measures the strength of the W2ISP signal, which is linked to the distance between the RFID and W2ISP antenna demonstrated in [17], [22], [23], [24] and [25]. The received signal strength is referred to in the RFID antenna as the RSSI signal [27] and recorded with an antenna ID (aID) that got a specific read from W2ISP. Thus, a single sensor monitoring can be represented by some attributes \{af, av, al, Received Signal Strength Indicator (RSSI), F(frequency), Phase (ϕ), aID\}. The reading sensor range is 4m as the maximum distance [30]. So, it attached precisely at the high level of the chest on the top of volunteers' clothes.
The two clinical rooms (RoomSet 1, RoomSet 2) designed to have three antennae in one room and four in the other room. Those sensors distributed around the places that the patients spend the most time (precisely toward the bed, chair, and walking area because these are high-risk places to fall elders) [31]. The RoomSet 1 has four antennae: (one at ceiling level and the rest on the wall) which used to sense the whole room. The RoomSet 2 includes three antennae has (two at ceiling level and one on the wall). In this room, these sensors focus on the areas that participants used (Figure 3).

3.2 Dataset:

In this experiment, the dataset that used presented in [17], [22], [24] and [25]. It is collected to recognize the ambulatory movement for seniors to administer our solution. The older people did in this dataset four types of activities. These are sitting on a bed, lying, ambulation and sitting on a chair. As shown in (Figure 3) this dataset was carried out in two clinical rooms sitting at the Elizabeth hospital [RoomSet1 and RoomSet2]. Each room has some RFID sensors distributed in different places inside the rooms.

The first one was provided with four RFID sensors placed on the ceiling of the bed, and the remaining sensors are attached to the wall next to the chair and the area near the bed (figure 3a). In the second room, [22] was equipped with three reader antennas of RFID type. They placed as follows: the two of them were attached on the top of the bed to provide better collecting signals while the rest placed on the wall in front of the chair (figure 3b). These two clinic rooms designed differently. Roomset1 provided by four RFID sensors and distributed to illuminate the whole place. However, Roomset2 has three of the same sensors that used in the Roomset1, to clarify just the areas where participants liked to spend their time during a day. In both rooms, the RFID sensors placed in different levels of rooms to avoid the noises or error signals. Error signals may happen because of the obstructions that may locate at clinic rooms. The obstruction may affect the data collected from the RFID and W2ISP sensors [22].

About 14 healthy older volunteers, who have aged (66-86 years), participated in this experiment. They are four male and ten females. Each one put a W2ISP sensor at the high level of their chests (Figure 4a). This sensor helps to capture the movement signals that are necessary to recognize the mentioned activities.
Because of a patient can do a limited set of movements, each one of participate requested to do the four sequential activates which are addressed above (sitting on a bed, lying, ambulation and sitting on a chair). For instance, older people may need to take a rest, so they will be lying on their bed or sitting on the chair. Also, when they want to have their foods, they will be sitting on a chair or bed. So, there are ongoing activities the elder need to do during their lives, and these are more importing for elder monitoring settings system. All these data collected using a particular application. During the data collection stage, the participants did not use blankets because the presence of quilts does not effect on the sensor tag energy [24].

As shown in Table 1, the activities that distributed in two sets of data. Each one has the class labels that distributed unevenly, and the unbalanced nature is more prominent in Roomset2. Where the sensor observations for lying on the bed at the clinic Roomset2 are more than 90% compared with the other sensor observations at the Roomset1. Both sets of data represent significant variations in the sampling rate. For Roomset1 and Roomset2 means time denseness among samples 0: 368_2: 438 s and 0: 720_9: 717 s respectively [24].

Table 1. Distribution of the activates in dataset with the Percentage

|               | Sitting on bed | Lying      | Ambulation | Sitting on chair |
|---------------|----------------|------------|------------|-----------------|
| Roomset1      | 15162 (25.89 %)| 30983 (59.04 %) | 1956 (3.73 %) | 4381 (8.35 %)   |
| Roomset2      | 1253 (5.53 %)  | 20529 (90.65 %) | 334 (1.47 %)  | 530 (2.34 %)    |

3.3 CNNets’ Architecture for (AR) system Dataset:

The study proposed a new solution for the Activity recognition (AR) system by using data that described in [see session 3.1.b]. This proposed solution dealt with the activities that considered the high risk of falling older people who lived without a supervisor [32]. The falling activities include a sequence of movements (see Figure 4) that captured from the antennae that distributed in the two clinical rooms at the Elizabeth hospital in Australia (see Figure 3). An observation sequence of a sensor is (Equation 1 and 2):

\[ X = (X_t)_{t=1}^{T} \]  
\[ Y = (y_t)_{t=1}^{T} \]

Where \( X_t \in \mathbb{R} \) and \( T \): the length of sequence. The AR system is to predict an activity label:

\[ Y = (y_t)_{t=1}^{T} \]

Where \( y_t \) is classes of activities such as (sitting on bed, lying, Ambulation and sitting on chair). As shown in the Figure 5, the proposed system used the Convolution Neural Networks (CNNets) methodology. It consists of three main layers (input, hidden and output layers) and some activation layers (Tanh, Softmax, ReLU, etc.) (see the equations 3, 4 and 5). As shown in table 4, our network contains...
18th main layers and activation layers. The activation layers that are between our main layers are to translate the input signals to output signals for training our data [33]. The equations for these layers are [34]:

\[
\text{Tanh}(X) = \frac{1}{1 + e^{-X}} \quad (3)
\]

\[
\text{Softmax}(X) = \frac{e^{X_i}}{\sum_{k=1}^{K} e^{X_k}} \quad \text{for}\ i = 1 \ldots K \quad (4)
\]

\[
\text{ReLU}(X) = \begin{cases} 
0 & \text{for } X < 0 \\
X & \text{for } X \geq 0 
\end{cases} \quad (5)
\]

Where X is an input from an observation sequence of a sensor or a previous layer:

The signals of AR are high quality by using CNNets because it has processing unite in the hidden layers [35]. This unit is responsible for characterizing the nature signals of antennae for AR. The input layer is called the convolutional layer. It takes input data and convolves with a special filter (kernel) as the equation below to:

\[
Y_{ij}^{xd} = V(b_{ij} + \sum_{m=0}^{M} \sum_{p=0}^{P} K_{ijm}^{p} Y_{(i-1)m}^{x+p,d}) \quad \forall d = 1, \ldots, D \quad (6)
\]

Where \(Y_{ij}^{xd}\) the output of Conv. Layer, \(V\) is a hyperbolic tangent function, \(b_{ij}\) is the bias for a feature map, \(m\) indexes over the set of feature map in the previous output layer, and \(K_{ijm}^{p}\) is the value at the position \(p\) of Kernel.

The hidden layer (Figure 6) is called the down sampling or pooling layer. It responds to minimize the resolution of feature map, and helps to increase the invariance of features to distortion on the output of the previous layer.

![Figure 5: Illustrate the CNNets structural](image)

![Figure 6: max pooling operation](image)
The fully connected is a hidden layer in CNNets. Fully connected layer aims to map an activation volume from the previous output layers into a class probability distribution. As a result of this layer is defined as:

\[ Y_i = \sum_{j=1}^{m^{(l-1)}} W_{ij}^{(l)} X^{d(l-1)} \]  

(7)

Where \( W_{ij}^{(l)} \) is the weight parameters which the fully connected layer tunes to create a stochastic probability of each class based on the previous output layers in CNNets methodology [36]. The \( Y_i \) values that are derived from the last hidden layer consider the output layer for CNNets.

### 4 EXPERIMENTS AND RESULTS

In this study, the dataset described in (see section 3.1) used. It tested the CNNets methodology to evaluate AR performance depending on what other proposed solution that used the same data [17], [22], [23], [24] and [25] in the table 2. Our experimental results are mostly depended on some factors. In instance of that the distance between antenna that would effect on the translation, a body motion of the sensor holder, and the multipath at a RoomSet also could effluence in such way on the reading rate for antenna due to the inadequate power supply for these antennae.

At the prediction stage, a new reading rate is obtained by the sensors, where it is used to predict falling detection activities for elders. In the training stage, we implemented the CNNets on 70% of data from each RoomSet. Our result of building the CNNets' network as shown in table 4 and the filter size that used was 3x3 due to the experiment in the study [35]. We trained on (15745) of (36736) samples from RoomSet1 and (6794) of (15851) samples from RoomSet2 datasets in 300 of epochs for each RoomSet data. This experiment built based on the Keras library for deep learning machine [37], [39-42] that finds in Python. The CPU is Intel core i5 that used with this experiment which takes a lot of time to implement the system compare to the GPU. The memory size is 8 GB 1867 MHz DDR3, and the operating system is OS X El Capitan ver. 10.11.6. The random gradient used to train the whole CNNets' network. In the testing stage, we also used CNNets to test this system on 30% of the data from each RoomSet in the same number of epochs.

| Method                              | Roomset1 | Roomset2 |
|-------------------------------------|----------|----------|
| **CNNETS**                          | **96.37** | **98.37** |
| Activity windowing (AW)             | 98.1     | 97.7     |
| Fixed sample windowing (FSW)        | 72.5     | 91.8     |
| Time weighted windowing (TWW)       | 73.1     | 91.7     |
| Mutual information windowing (MI1)  | 70.8     | 94.4     |
| Mutual information windowing (MI2)  | 70.8     | 93.8     |
| Dynamic windowing (DW)              | 74.7     | 94.6     |
| Fixed time windowing (FTW)          | 78.2     | 92.3     |
| FTW+MI1                             | 71.5     | 91.7     |
| TWW+MI1                             | 77.1     | 95       |
| Weighted support vector machines (WSVM) | 93   | 94       |
| Sequence learning classifier        | 94       | 96.1     |
| Conditional random fields           | 84.55    | 86.9     |
As a result of our proposed system, we observed that both the RoomSets achieved the highest accuracy comparing with the other proposed solutions (see table 2). Also, we concluded that the room with the smaller number of antennae produced higher accuracy than another room due to the places that these antennae attached inside. These areas that the seniors like to spend time during the day. (As shown in Figure. 7 and table 3), the lying activity in both datasets achieved the highest prediction than the other activities. Since the distances between WISP that the participants wore it and the antennas caused an error in reading. Additionally, the folds in the volunteers' clothes could be impeded reading rate, or other parts of their bodies could block RF signals that come from the sensors [25].

The results indicate that RoomSet1 achieves accuracy 96.37% with baseline error 3.63%, and RoomSet2 achieves accuracy 98.37% with 1.63% error. These results proved that this system is able to indicate the difference between activities that a patient does during the day.

![Figure 7: AR recognition performance for RoomSet1 & RoomSet2 configuration](image)

| TABLE 3. THE PERCENTAGE OF PREDICTION ACTIVATES IN CNNETS |
|----------------------------------------------------------|
| sitting on bed | lying | ambulating | sitting on chair |
|----------------|-------|------------|------------------|
| RoomSet1       | 29%   | 62%        | 1%               | 8%               |
| RoomSet2       | 5%    | 94%        | 1%               | 0%               |

| Table 4. CNNets Network in this experiment |
|--------------------------------------------|
| LAYER (TYPE) | OUTPUT SHAPE | PARAM # | CONNECTED TO |
|---------------|--------------|---------|--------------|
| CONVOLUTION1D_1 | (NONE, 9, 32) | 128 | CONVOLUTION1D_INPUT_1[0][0] |
| ACTIVATION_1 | (NONE, 9, 32) | 0 | CONVOLUTION1D_1[0][0] |
| DROPOUT_1 | (NONE, 9, 32) | 0 | ACTIVATION_1[0][0] |
| MAXPOOLING1D_1 | (NONE, 4, 32) | 0 | DROPOUT_1[0][0] |
| CONVOLUTION1D_2 | (NONE, 4, 32) | 3104 | MAXPOOLING1D_1[0][0] |
| CONVOLUTION1D_3 | (NONE, 4, 32) | 3104 | CONVOLUTION1D_2[0][0] |
| ACTIVATION_2 | (NONE, 4, 32) | 0 | CONVOLUTION1D_3[0][0] |
| DROPOUT_2 | (NONE, 4, 32) | 0 | ACTIVATION_2[0][0] |
| MAXPOOLING1D_2 | (NONE, 2, 32) | 0 | DROPOUT_2[0][0] |
| FLATTEN_1 | (NONE, 64) | 0 | MAXPOOLING1D_2[0][0] |
5 CONCLUSIONS

Monitoring elders is one of the main issues in the past years because of loses in souls and finance that caused by falls and recorded in the human clinics and hospitals. In this research two sources of information were available to collect data. A multiple wearable triaxle accelerometer sensor W^2ISP that can be connected to a single RFID sensor, where RFID used the air interface protocol to communicate with the W^2ISP.

Elders can move in limited movements so only four movements were collected from healthy participant elders. The movements were sitting on bed, lying, ambulating and sitting on chair which considered as a key point that could cause danger for elders. To monitor the participants, a system designed in two rooms. The first room had four sensors. The second room had three sensors. The sensors installed around the spaces where the participants spend the most time. Deep learning was used to recognize the collected data while Random gradient used to train the whole CNNets network. From the data recognition this experiment found that laying activity had the highest prediction than other activities in both rooms. The final results in this research concluded as: room1 accuracy was 96.37%, error 3.63% and room2 accuracy was 98.37%, error 1.63 using a one-dimension array and keras as a library. The outcome that achieved in room2 was higher than room1 because the distribution of the RFID sensors. Finally, this study achieved higher accuracy than other studies that used the same dataset.

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