An Application of Human Fall Prediction Using Convolutional Neural Network

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Ayesha Butt[1], Sanam Narejo[2], M. Moazzam Jawaid, Arbab Ali Samejo[4]

[1,2,3,4]*Department of Computer Systems Engineering Mehran University of Engineering and Technology*

Abstract: Falls are major problem especially in elderly people that causes major health problems. It became a source of deaths, internal injuries, and a loss of anatomy. Therefore, comprehensive research is required in predicting the falls, on the right time. Or Timely prediction of falls can minimize the death or injury rate as well. Moreover, it is shown that most of the falls detection methods having deep learning methodologies. And in our research, we used most effective and useful deep learning method for fall detection that is CNN (Convolutional Neural Network) with two publicly available datasets that is URFD. Our experimental results shows that CNN performed well in terms of accuracy. The result of research proved that CNN is the best model with 80% accuracy.

Keywords: *Fall prediction, Convolutional Neural Networks, Deep learning, Activities of daily living,* Internet of things, Machine learning

1. Introduction

In this era, Internet of things (IoT) has possessed various tasks, that are used to performed so many scientific research that are associated with data mining and different machine learning techniques, that shows the remarkable impact on society. According to WHO research, around 35% elderly people aged 65 or >65 fall each year, and number of falls increases slowly and gradually [1]. And number of elderly people increases day by day as well, in China figure show that in the end of 2021 it will rise by 35% [13]. In Canada population of elderly will be about 20% by 2026 [14]. It was observed that 60% of population of the elderly who lay on the floor for more than an hour right after the incident of falls, they may die within few months [15] Therefore, the rate of deaths increases day by day. So, an immediate and urgent development of system is required.

Wearable sensors i.e. accelerometer and gyroscope [4] are used to detect different falls. In the past era, most of the researchers focused on secure and reliable systems that are less computational as well to monitor the falls events in elderly

Falls can be easily monitored by attaching different types of sensors at different places of body. Research shows that mostly authors used machine learning [16] algorithms and techniques for classification problems. In this paper we used Convolutional neural network (CNN) with publicly available dataset i.e. URFD. And observed that URFD work well with CNN and achieve better accuracy as compared to other proposed systems.

These thoughts have make the research strong on fall detection to enable fast and proper assistance to the elderly detection. The most common policies consist in a combination of sensing and computing technologies to collect relevant data and develop algorithms that can detect falls based on the collected data [3]. These approaches have led to the appearance of Smart Environments for elderly assistance, which had been traditionally limited to home settings [4]. However, we believe that, with the irruption of the paradigm of the Internet of Things (IoT) [5], the possibilities to extend Smart Environments, and more specifically fall detection approaches, grow considerably

In non-wearable devices, single or multiple sensors such as optical cameras [8], microphones [9], or microwave radars [10], are applied in the target environments to detect fall. However, the performance of optical camera monitors are quite sensitive to light intensity, and the microphones require quiet environments to ensure the detection accuracy.

In contrast, microwave radar is much more adaptable to bad environment due to not being performance-affected by light and sound noise. However, the microwave characteristics of human action are not robust enough due to the range and Doppler resolution limits of radar system. To improve the fall detection performance and the environmental adaptability, different kinds of sensors can be used simultaneously to obtain and fuse multi-sensor information. However, by now, multi-sensor system for fall detection based on radar and optimal sensor are seldom mentioned in the existing literatures [11].

There are few reasons because of that we choose convolutional neural network in our research.

A CNN based novel method for mismatch detection in hyperspectral images is proposed which detects mismatch by classifying the pixels based on their spectral responses. The optimum architecture of CNN for this purpose is determined by experimenting six different architectures with different number of layers with different filter sizes in the convolutional layers. The optimum architecture contains four convolutional layers each with a filter size of 3x3 is determined in fig.4

The proposed method achieved the highest accuracy (80% on the URFD database among the former methods of fall detection

Corresponding author Email address*: aishabutt004@yahoo.com*

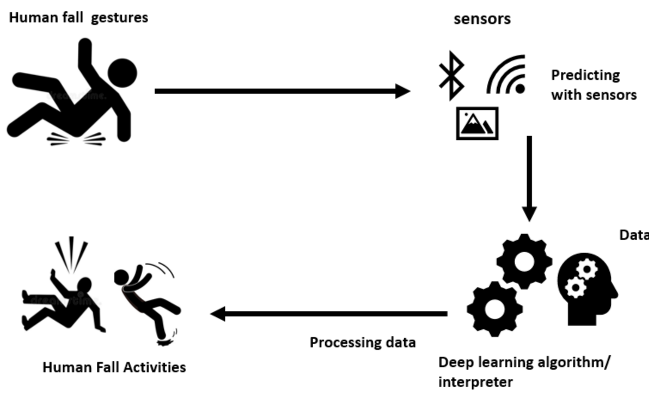

Fig.1 depicted the falls system

Figure 1 shows the overall depiction of the system, first the event occur then how sensors will detect the events then with the help of preprocessing techniques and machine learning algorithm falls detects.
Moreover, rest of the paper is organized as follows: section II presents the methodology of our research, section III shows the experimental results and section IV concludes the paper.

2. Related Work

In related work most of the authors used different Deep learning models to predict the falls. And mostly authors used machine learning algorithms for detecting falls, i.e SVM, KNN, CNN etc. most of the systems are threshold based [5]. In [6] authors proposed a system for fall detection with KNN algorithm. Most of the authors observe outstanding results with CNN. and they observe with CNN detection of falls are very effective. In this paper [7] author detect falls by using CNN. in this paper [8] researchers apply CNN (Convolutional neural network) with frames for the better accuracy. In this paper [9] author proposed a deep learning approach for detection of falls, the proposed system used cameras at different location in home to detect the falls. The main aim of this research [10] is to identify falls with three different components. i.e. feature detection, posture analysis and activity recognition. They used Hidden Markove Model (HMM), Support Vector Machine (SVM) for classification. They further explained a method of falls detection using an obtrusive motion. In this paper [11] author designed a system especially for those people who have some sort of illness or medical history, i.e autism, accident, injuries etc, they used pattern recognition classifiers for detection of falls.

Vishwakarma et al. [22] worked with bounding boxes to compute the aspect ratio, horizontal and vertical gradients of an object, and fall angle and fed them into a GMM to obtain a final answer. Many solutions are based on supervised learning, that is, extracting lots of features from raw images and using a classifier to learn a decision from labeled data. This is the case, for example, of Charfi et al. [17], who extracted 14 features, applied some transformations to them (the first and second derivatives, the Fourier transform, and the Wavelet transform), and used a SVM to do the classification step. Zerrouki et al. (2016) [23] computed occupancy areas around the body's gravity center, extracted their angles, and fed them into various classifiers, being the SVM the one which obtained the best results. In 2017, the same author extended his previous work by adding Curvelet coefficients as extra features and applying a Hidden Markov Model (HMM) to model the different body poses [14]. A less frequent technique was used by Harrou et al. [24], who applied Multivariate Exponentially Weighted Moving Average (MEWMA) charts. However, they could not distinguish between falls and confounding events, which is a major issue that is taken into account in our solution. In fact, not being able to discriminate between such situations produces a great amount of false alarms.

3. Methodology

Methodology of our work is briefly explained in this section. Following flowchart of the proposed work which has been followed for detection of falls.

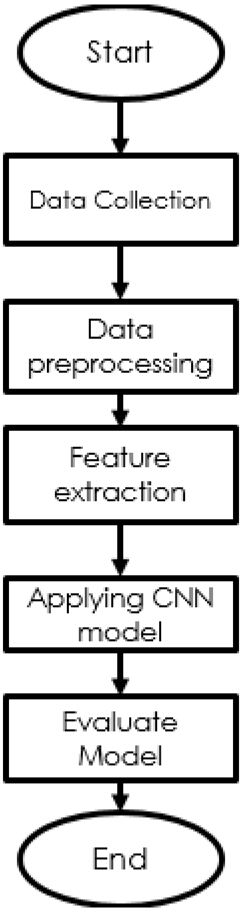

Figure.2. Flow chart of system

3.1 Data Gathering

Prior to anything the first step of the data driven modeling is to collect the appropriate dataset. The dataset that used in our research work is publicly available i.e., UFRD. The UR Fall detection [12] dataset contain 40 activities of Daily living and 40 Activities of falls.

Figure.3. Activities of daily living

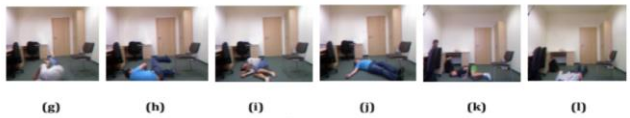

Figure.4. Falls events.

Figures 3 and 4 are showing ADL's and Falls events that Dataset is used.

Step 2: Data Preprocessing

Once the data is gathered, we progressed to the preprocessing of data. It is quite important to preprocess the data to get rid of the undesirable signals, noises and null values from the signals or data.

This supports for better classification by using the effective machine learning algorithm. We used Butterworth filter Infinite impulse Response IIR for the preprocessing. This provided a smoother signal, as well less computationally intensive.

Step3: Feature Extraction

Once the data is preprocessed, the next step is to extract the different features from the data. We extracted the four features from the preprocessed data. These features are minimum amplitude, maximum amplitude, mean, variance of the data. All these features are extracted from the three sensors, i.e., accelerometer, gyroscope, magnetometer along with x, y, and z axis.

Step 4: Applying a CNN model

For classification and achieving an optimal result, our main focus was to explore the performance of CNN. The aim was to achieve best possible accuracy and lowest error rate. The detail explanation of CNN is mentioned below. Finally with the help of CNN classifiers the prediction of falls is classified, and performance accuracy is measured.

4.1 Creating CNN model:

In mathematical CNN is shown as in equation 1, Convolutional is a function that driven from two functions by integration that tell us how the image is formed by other function.

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)\, g(t - \tau)\, d\tau \qquad (1)$$

There are few steps by which we can create the LSTM model very effectively.

Step 1: this is the first step in which the LSTM is to recognize that information that are not required and throw out from the cell. This decision has been taken by the sigmoid layer called as forget gate layer in LSTM as shown in "Eq (1)"

$$f_t = \sigma(w_f\,[h_{t-1}, x_t] + b_f) \qquad (1)$$

In Eq. (1), w(f) is a weight, h[t-1] is the output from the previous time stamp, x(t) is a new input, b(f) is the bias

Step 2: in this step, it is to decide that what new information we are going to save in cell, in this process sigmoid layer decides which value will be updated. Or the tanh layer create a new space for a new vector, as shown in Eq. (2) and (3)

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \qquad (2)$$

$$\widetilde{c_t} = tanh(W_c[h_{t-1,}x_t] + b_c) \qquad (3)$$

In this equation tanh is playing the role of creating the new vector. In the next step we will combine these two states

Step3: now in this step we will update the old cell state C(t-1) into the new cell C(t), first we have to multiply the C(t-1) by f(t), the things we forget earlier, forgetting those things again, then we add i(t) * c(t). by this we decide how much we update each cell state, as shown in the Eq. (4)

$$C_t = f_t * C_{t-1} + i_t\ * C_t^{\sim} \qquad (4)$$

Step4: In this step, sigmoid layer will run, that decide what parts of state of cell, is we're going for the output. As you can see in Eq(5).

$$O_t = \sigma(W_0[h_{t-1,}x_t] + b_0 \qquad (5)$$

Then we have to put the cell state through tanh and then we've to multiply it by the out of sigmoid gate, so that we have nly that output we have to decide to, as shown in Eq

$$h_t = O_t * \tanh(C_t) \qquad (6)$$

These are the major steps in creating the machine learning model Long short-term memory.

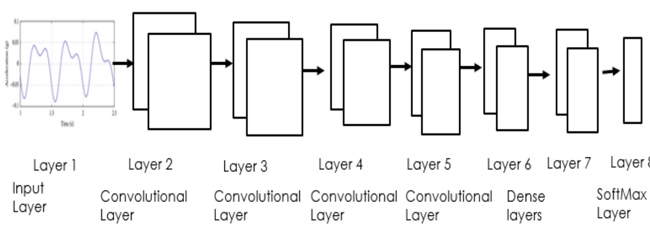

Figure.5. Depiction of CNN.

In this architecture 4 layers are used as convolutional layers and two layers are used as dense layers for feature extraction, For activation of CNN we used SoftMax because it converts output of the layers in neural network.

4. Results and Discussion

Parameter	Value
Number of CNN layers	1
Activation function	ReLU
Kernel size	(2, 2)
Optimizer	Adam
Epoch	50
Loss function	Categorical cross-entropy
Dropout	0.25, 0.5
Pooling window	Max pooling (2, 2)
Neurons at dense layer	512

Parameter	Value
Number of CNN layers	1
Activation function	ReLU
Kernel size	(2,2)
Optimizer	Adam
Epoch	50
Loss function	Cetegorical cross-entropy
Dropout	0.25
Pooling window	Max pooling (2,2)
Neuron at dense layer	500

The models used in our research were trained for 50 epochs with early stopping call backs (patience = 5 epochs). In order to find the best setting, different optimization techniques were applied to different settings of 2D Deep-CNN. The time required to complete one epoch was different for different settings. The model performance was calculated using loss and classification metrics, such as Precision, Recall, F1-measure and AUC-ROC curve. Fig. 5 shows the Proposed Deep-CNN structure with the introduction of Global Average Pooling Layer.
In this section, after the training and testing of the dataset, we discuss the accuracy and performance of the system.

After training the 80% of data and test the 20% of data and measured the performance through performance matric i.e.: sensitivity, specificity, and accuracy. Here we used URFD dataset for machine learning algorithm, we used CNN- with UFRD dataset, and we achieved an optimal result with this dataset.

1. Sensitivity (Se): tell us about the space of the system, to detects the falls. Basically, it is a ratio of true positive that correspond to the number of falls, mathematically it can be represented as an Eq (1)

$$S_{e}= \frac{TP}{TP+FN}\ x\ 100 \tag{1}$$

2. Specificity (Sp): It is the capacity of system that detect the falls when it occurs only, mathematically it can be represented as an Eq (2)

$$S_{p}= \frac{TN}{TN+FP}\ x\ 100 \tag{2}$$

3. Accuracy (Acc): tell the correct and differentiate between the falls and the non falls activities which is ADL, mathematically it can be expressed as an Eq(3)

$$A_{cc}= \frac{TP+TN}{TP+TN+FP+TN}\ x\ 100 \tag{3}$$

Here, TP is a true positive which means a fall occurs then algorithm detect it, TN is the True negative which means algorithm does not detect the fall, and it is not occur, FP is a false positive which means algorithm declare the falls when it is not occur, and FN is a false negative which means algorithm misses the fall when it is occur respectively. And there is an inverse relation between the specificity and sensitivity.

The cross-validation technique is used for testing and training the dataset, by this technique all the dataset is used for testing and training.

In the figure 6 we have set number of filters to 64, and one convolutional & max pooling layer (basic architecture) and train over model with 75 epochs which resulted in 80% accuracy on the other hand the validation accuracy is 80%.

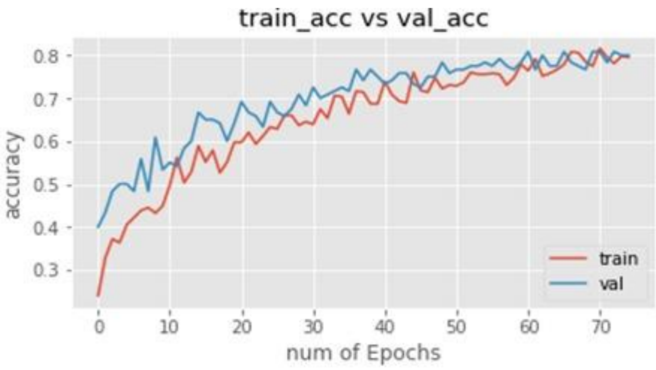

Figure.6. training and testing of CNN.

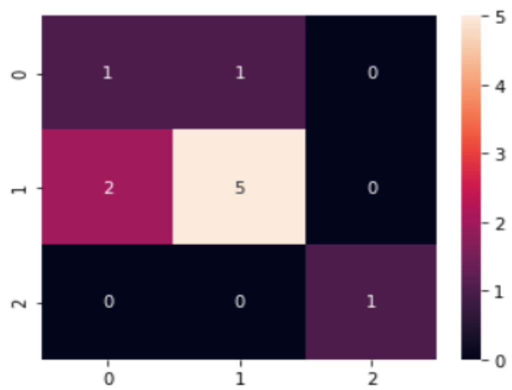

Figure.7. Confusion matrix on URFD dataset of the proposed method.

when dealing with multiple classes of similar shape, classifiers may be confused. Infected rice leaf images on different levels or backgrounds can cause high complexity which leads to lower performance for the patterns displayed in the same class. The classification accuracy of a model can be visually tested using a confusion matrix. The entire dataset of our study is split into a training set and a testing set randomly in order to train and test the model. To evaluate the proposed model, the 50% dataset is used to train and the remaining 50% dataset is used to test. Total 8,400 observations are utilized for training the model, whereas another 8,400 observations are utilized for testing the model. Figure 9 displays the final test results confusion matrix. The deeper the color in the visualization results, the greater the model's accuracy in the respective class. All correct predictions are located diagonally, whilst all wrong predictions are off diagonal. The classification accuracy can be visually assessed based on these findings.

5. Conclusion and Future Work

In this research, we proposed an effective machine learning algorithm by using the Convolutional Neural Network (CNN) to predict the fall detections effectively. The proposed methodology used the simple feature extraction from the publicly available dataset. These extracted features are used to train and test the machine learning model CNN 80% and validation accuracy is 80%.

The proposed system is used for effectively in detection the falls. Future work includes the hardware implementation of the system in clinically sectors.

The obtained output is the highest compared to the other methods that have been used to detect falls. So, that the system robustness is evaluated, no fine tuning was carried out. The dataset that was used allowed the researcher to obtain an average score of 92.3%, which is an improvement on the previous system that were compared to (Camplani and Salgado, 2012). This result can potentially increase if no hardware limitations are encountered. As for future work, other methods, other than CNN, are going to be used to test their efficiency in fall detection and check whether or the results gotten using CNN can be improved. In addition, other body postures, other than falls, will be closely studied in order to implement a powerful algorithm for detection purposes.

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