

Detection of Human Activities and Human Fall Recognition Using Deep Learning Techniques

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Abstract: Smartphones are quickly becoming the most important communication device in people's lives in today's world. Human Activity Recognition has grown in popularity as a field of study in a variety of areas, including medical care, tracking, and education. The sensors in smartphones allow us to use them for a wide range of applications. Healthcare is one of the major domains where human activity recognition is widely used. In this paper, a human activity recognition system has been developed that can detect six activities of daily living (ADL) along with human fall. Human fall occurs due to an accident that can cause serious injuries which may lead to significant medical problems when the issue is not addressed properly. The proposed system uses a variant of deep learning technique to detect human activities and human fall. The accuracy is significantly increased by nearly 4% when compared with previous results.

Keywords: Activities of Daily Life; Smartphone sensors; Accelerometer; Gyroscope; Movement monitoring ; Healthcare; Bidirectional LSTM.

1. INTRODUCTION

In recent times, smartphones have become an indispensable part in the life of humans. The daily routine of an individual can be captured by using smartphones. The accelerometer and gyroscope are the most widely used sensors. The in-built sensors in smartphones enable us to track the individual's movement. This information can be utilized to recognize several day-to-day routine activities like standing, walking, laying, sitting, walking upstairs and walking downstairs[2]. The same information is also utilized for detecting human fall. Data from a person's daily life may be used to investigate their way of life and the sequence of their bodily activities. Since lack of physical activity causes the majority of chronic diseases, tracking everyday movements will quickly identify any deviations from normal activities. Identifying human falls will also assist in providing appropriate assistance to those who are in need. HAR has numerous applications in the various fields such as elderly care, monitoring the patient, education, military, and rehabilitations [2][3][8].

This paper proposes an enhanced human activity recognition model for fall detection using modified Bidirectional Recurrent Neural Network (BRNN) incorporated with Long Short-Term Memory (LSTM), a Deep Learning (DL) approach. First of all the data for the proposed system is collected from the smartphone sensors such as the accelerometer and gyroscope. Secondly, the data is then preprocessed and segmented. Then the system is trained and tested for six human activities including fall. The Mobifall dataset which contains sensor data of 66 subjects performing four different falls and twelve different ADLs is used. Finally, metrics like accuracy, f-measure, precision and confusion matrix are used to measure the performance of the system[2][3][8].

2. RELATED WORK

Variety of sensors is used to gather the input data. The next step is pre-processing which helps in elimination of noise and dealing with erroneous values which can be done by applying data cleansing methods. Cleansed data is then segmented into windows. Segmentation of windows is done using many ways like sliding windows, event based windows and energy windows. Following the completion of pre-processing and segmentation, feature extraction is performed to improve the performance of classification algorithms. To accomplish this task, deep learning methods are used [2][3]. The features extracted are used to classify the activities using various classification algorithms and metrics such as accuracy, F1-score, precision and confusion matrix are used to assess the system's performance [1][2][3].

3. ILLUSTRATION OF THE PROPOSED SYSTEM

The proposed system is evolved using BRNN and LSTM. It has two hidden layers and 30 neurons. Each module in the system is explained as follows.

3.1. Recurrent Neural Network (RNN)

RNN algorithm is used to solve problems involving continuous data. As HAR is a time series problem, the input is in sequential form. It comprises three layers - i/p, hidden, and o/p, with hidden layers containing several nodes. Figure 2 shows the visual representation of a RNN node. The present hidden state value h_t and the output value o_t is generated by the generating function of each hidden node t is calculated using formula:

$$h_t = \varepsilon(whhht_{-1} + wihxt + bh) \quad (1)$$

$$y_t = \varepsilon(whoht + bo) \quad (2)$$

where, x_t = new input state, h_{t-1} = old hidden state, h_t = new hidden value,

whh = hidden-hidden state weight, wih = input-hidden state weight, who = hidden-output state weight, bh = hidden state bias, bo = output state bias, o_t = new output state, ε = activation function. ε is called an activation function.

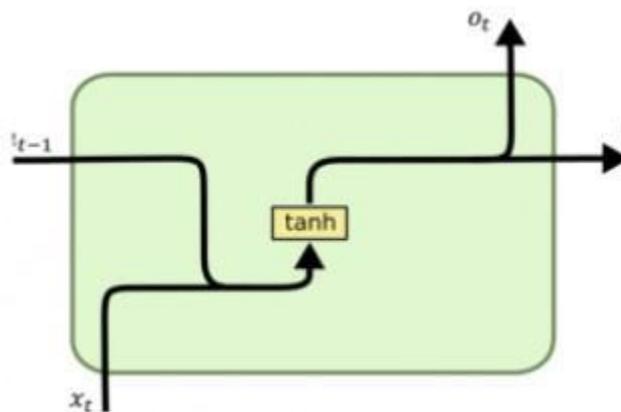


Fig. 1: Sample Node of Recurrent Neural Network (RNN)

3.2. Long Short Term Memory (LSTM)

The main drawback of using RNN is its inability to handle exploding and vanishing gradients which decreases the performance of the network model in wide-range of temporal dependencies between inputs and human activities. Use of LSTM enables us to overcome the drawback of RNN, by using LSTM memory cells instead of RNN nodes. LSTM memory cells are shown in Figure 3. Each memory cell's characteristics are administered by the gates in LSTM cells. The activation functions of gates control the state of each cell. Input gate, forget gate and output gates are the gates to which the input values are fed. Activation function is represented by the symbol ε . The following equations show each timestep(t) calculation of hidden state value.

3.3. Proposed modified BRNN-LSTM Model

Accelerometer and gyroscope readings are splitted into fixed size window T with 128 timesteps. The neural network input consists of reading $(y_1, y_2, y_3, \dots, y_{T-1}, y_T)$ obtained at time T , where y_T is the reading obtained at any time instance t . The readings from the windows that are segmented are then given to the modified BRNN-LSTM network. The output is combined to single final output from different states using Rectified Linear Unit (ReLU). The model is compiled using categorical crossentropy and adam optimiser is used.

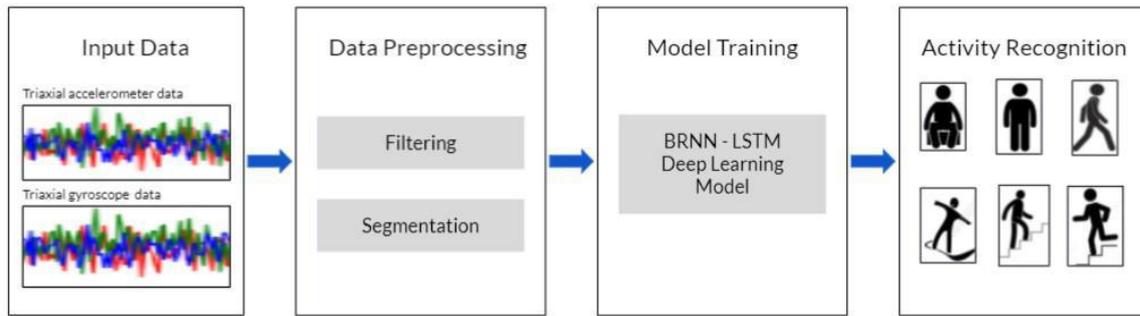


Fig. 2: Proposed System Design

4. EXPERIMENT AND EVALUATION

The enhanced human activity recognition system for fall detection is executed using python 3.5 and tensorflow 1.7.

4.1. Dataset Description

Data from the accelerometer and gyroscope sensors of a smartphone were recorded. Mobifall is an open-source dataset that contains data gathered from a smartphone as participants engage in a variety of activities and fall. The data set comprises four types of falls, twelve distinct ADLs obtained from a total of 66 subjects. The tabulated description of the activities recorded are shown in Figure 6 shown below. The ADLs are divided into three sections such as mentioned in Figure 6.

Data set is taken from the URL <https://bmi.hmu.gr/the-mobifall-and-mobiact-datasets-2>.

Dataset	Simple Movements	Standard Normal Life Movements	Sporting Activities	Falls
MobiFall & MobiAct	<ul style="list-style-type: none"> - Sitting on a chair - Stepping in a car - Stepping out of a car - Standing 	<ul style="list-style-type: none"> - Normal walking - Going downstairs - Going upstairs 	<ul style="list-style-type: none"> - Jogging - Jumping 	<ul style="list-style-type: none"> - Forwards (use of hands to dampen fall) - Forwards (first impact on knees) - Sideward bending legs - Backward (while trying to sit down)

5. RESULT ANALYSIS

This section presents the evaluation results of the proposed system. The confusion matrix of the system is shown in figure 7. This matrix shows the relation between correctly and wrongly predicted activities. In the confusion matrix, TP (True Positive) represents the number of positive activity predictions that are correctly predicted whereas FP (False Positive) gives the value for number of positive activity predictions that are predicted as negative. Similarly, TN (True Negative) is the number of negative reviews correctly predicted and FN (False Negative) is the number of negative activity predictions predicted as positive. The proposed system achieved an overall accuracy of about 91% and good accuracy for activities like sitting, walking and fall. The metrics calculated for each activity is shown in table 3.

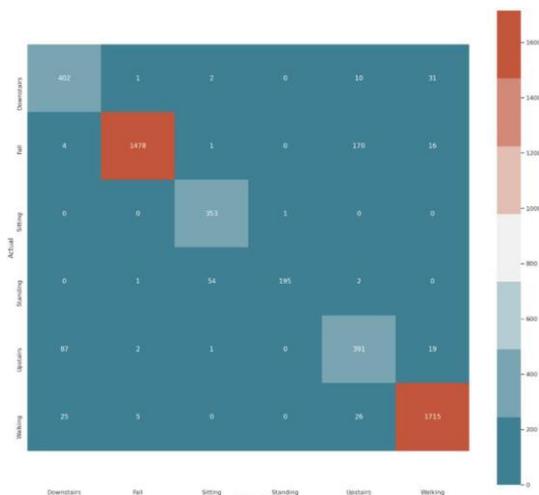


Fig. 3: Confusion Matrix

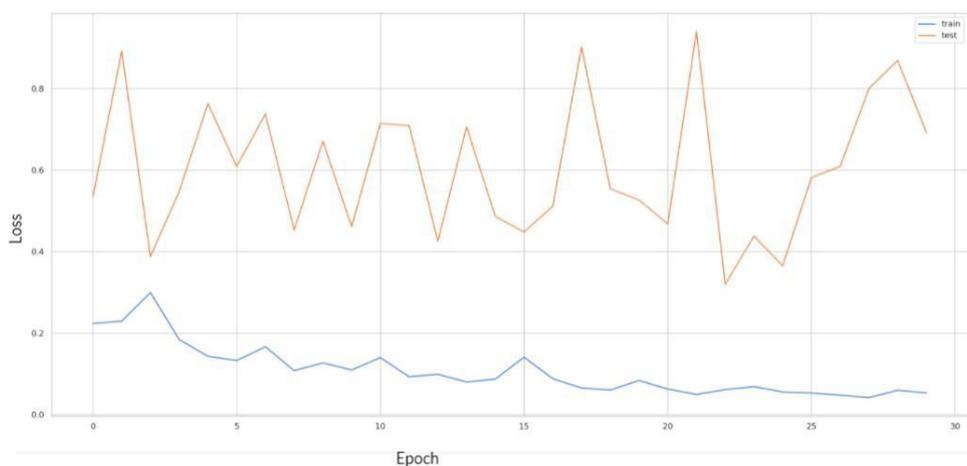


Fig. 4: Training progress vs Epochs

6. CONCLUSION

The HAR system using modified BRNN-LSTM for fall detection is developed in this paper. The system is able to predict five different activities along with fall successfully. The developed system produces nearly 4% more accuracy than many of the existing machine learning and deep learning methods by extracting the most representative features from the data. Future directions can be included with more complex activities for recognition and also be extended to support multi-sensor data.

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