Human Activities Recognition Using Acceleration Data from A Smartphone

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Abstract: Human Activity recognition is one of the most important tasks in many fields, in which it aims to provide information about human physical activity. In particular, the human activity recognition can be used in medical diagnoses, crime monitoring, and keeping track of elderly people such as whether the walking, sitting, standing or walking upstairs or walking downstairs in which people move. For example, ascending or descending stairs can be a risky activity for people with cognitive disorders because of a possible fall, which can have more serious consequences than if it happened on a flat surface. In the present study, we make a comparison between different machine learning algorithm in way to recognize human activity using acceleration data obtained from a smartphone placed in the pocket of people is introduced. The acceleration signals were filtered, smoothed, and segmented based on Windowing techniques. Subsequently, some features of each segmented signals were extracted, which was used to train six classifiers using the Support Vector Machines, Naive Bayes, Decision tree, Random Forest, K-Nearest Neighbors, and CNN algorithms. Data was collected from Five adult subjects who performed five Human activities: (I) Sitting, (II) Standing, (III) Walking, (IV) going downstairs, and (V) going upstairs. The results illustrate the viability of using the proposed method and technologies as life assistant.

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1. Introduction

Human Activity Recognition (HAR) has become one of the most trending research topics due to availability of sensors and accelerometer which comes with every smartphone, (HAR) aims to provide information on human physical activity, which can be used in medical diagnosis. For keeping track of elderly people, and assistance for people with cognitive disorders, HAR can be used. HAR can be used to control crime rates by monitoring. Daily activity recognition can help to establish a smart home environment.

In HAR, many human activities such as walking, jogging, standing, sitting, downstairs, upstairs, etc. are recognized. External and wearable sensors are the two basic methods for deploying HAR systems. In the external approach, the monitoring devices are set at fixed points, and users are expected to interact with them. The vision-based technique, for example, is one of the well-known external methods for human activity analysis that has been extensively explored. In terms of coverage, accuracy, privacy, and cost, however, it confronts numerous hurdles. It necessitates infrastructure assistance, such as the costly installation of video cameras in surveillance areas. Furthermore, cameras will not be able to acquire any data if the user performs outside of their reach. On-body sensors such as accelerometers, gyroscopes, and magnetometers are used in the second approach to convert human motion into signal patterns for activity recognition.

Smartphones contain sensor as accelerometer and gyroscope, this sensor help capture human activities. In this study, we classified common human activities from the collected dataset from flutter application through use of different machine learning algorithms.

The paper is divided into various methods for human activity recognition and the challenges for activity recognition. Section 2 describe literature review Section 3 describes related work and what we take from these works. Section 4 describes methods. Section 4.1 describes preprocessing techniques used for data such as filter and smooth data. Section 4.2 Preprocessing. Section 4.3 describes Segmentation of data. Section 4.4 describes feature extraction stage in which we extract 18 features. Section 4.5 describes the review and comparison of machine learning methods for HAR such as K-nearest neighbors (KNN), decision trees, support vector machines (SVM), random forest, naive bayes, and CNN. At last, in section 4, the open issues and challenges for activity recognition are described. Finally, section 5 explains results, discussion, and conclusion.

2. Literature Review

2.1 Recognition of Gait Activities Using Acceleration Data from A Smartphone and A Wearable Device

Human activity recognition using acceleration data was illustrated in many papers and one of these papers was named "Recognition of Gait Activities Using Acceleration Data from A Smartphone and A Wearable Device". In this paper to reach the goal of recognizing human activity they went through many phases first in the data acquisition phase, they used smart phoneaccelerometer and an IMU sensor to collect the data which was used to recognize human activity. They extracted two types of data from the smart phone accelerometer and the IMU which are XYZ, and Forward Direction data. Then in the preprocessing phase a low pass filter was used in the acceleration signal. After that a smoothing pseudo-gaussian function is applied the sack of smoothing the acceleration data. Then they started to segment the acceleration data based on the strides they have detected using smoothed data. And last they used 4 classification algorithms to recognize human activity. These are the results of each algorithm using the XYZ data, FD data, and Poth the XYZ and FD data together.

Table 1. Correctly classified instances (%) using acceleration data from smartphone and IMU. NB: Naive Bayes; SVM: Support Vector Machines; and KNN: K-Nearest Neighbors.

Device	Treatment	Features	NB	C4.5	SVM	KNN	Avg (σ)
Smartphone	acc_{FD}	5	53.4	67.6	50.3	68.6	60.0 (9.5)
	acc_{XYZ}	5	52.8	61.4	50.0	58.6	55.7 (5.2)
	$acc_{FD} + acc_{XYZ}$	9	61.0	63.8	61.4	**79.3**	66.4 (8.7)
IMU	acc_{FD}	5	60.0	63.8	58.6	81.0	67.1 (10.3)
	acc_{XYZ}	5	50.7	68.6	49.7	75.9	61.2 (13.1)
	$acc_{FD} + acc_{XYZ}$	9	59.7	68.6	63.8	**85.5**	69.4 (11.4)

Table 2. Classification results for each gait activity using the data treatment $acc_{FD} + acc_{XYZ}$ and the KNN algorithm. TPR = true positive rate; TNR =true negative rate.

	Smartphone		IMU	
Gait Activity	TPR	TNR	TPR	TNR
Going down an incline	0.871	0.964	0.871	0.959
Going up an incline	0.900	0.964	**0.900**	0.918
Walking on level ground	**0.914**	0.900	0.800	**0.982**
Going down stairs	0.600	**0.972**	0.825	0.980
Going up stairs	0.450	0.940	0.875	0.976
Weighted average	0.793	0.946	0.855	0.960

2.2 Human Activity Recognition using Deep Learning Models on Smartphones and Smartwatches Sensor Data

Another method of recognizing human activity is by using phone and watch accelerometer and gyroscope X, Y, and Z-axis was mentioned in the "Human Activity Recognition using Deep Learning Models on Smartphones and Smartwatches Sensor Data" paper. The raw data of the three axes were segmented into 10 second data without over lapping. In the feature extraction phase, they made binned distribution, average, standard deviation, variance, average absolute difference, and time between the peaks for each axis. Then they started classificationphase using 4 classification algorithms which are LSTM, BILSTM, Convolutional LSTM, and CNN algorithms. They aimed to classify 18 human activity including walking, jogging, walking up the stairs, sitting, standing, typing, brushing teeth, eating soup, eating chips, eating pasta, drinking,eating sandwiches, kicking, playing catch, dribbling a ball, writing, and clapping. The results of the classification algorithms were as follows.

Table 3: The Macro-F1 values of different classifiers for **watch** sensor data.

Models	Accelerometer	Gyroscope	Both
CNN	**0.849**	**0.687**	**0.774**
BiLSTM	0.848	0.617	0.721
ConvLSTM	0.843	0.658	0.754
LSTM	0.825	0.627	0.743

Table 4: The Macro-F1 values of different classifiers for **phone** sensor data.

Models	Accelerometer	Gyroscope	Both
CNN	0.796	0.387	0.631
BiLSTM	0.773	0.429	0.611
ConvLSTM	**0.814**	**0.432**	**0.638**
LSTM	0.756	0.395	0.743

1. Related Work

Many Human Activity Recognition have allowed the concept of collecting data of various human activities from many ways such as video cameras, environmental sensors, and portable devices. In our system we used portable devices due to the availability of many sensors such as accelerometer and gyroscope and they work in outdoors, and they are not sensitive to occlusion or lighting. The most known human activities are walking, jogging, sitting, standing, upstairs and downstairs. There are many authors who spoke about the recognition of the mentioned human activities, for example, In [1] authors used one-dimensional (1D) Convolutional Neural Network (CNN)-based method to recognize these activities using accelerometer data collected from smartphones sensors and its raw acceleration signals are combined in a vector magnitude and segmented in windows of 10 and 20 s.

In [1] a different study, they classified walking into three speeds which are: slow, normal, and fast. Accelerometer data were collected from 25 subjects using smartphones sensors where eight features were extracted from magnitude vector and seven classification techniques were applied to classify walking data based on the mentioned speeds. In [1], Naive Bayes classifier (NB), decision tree classifier, Support vector machines (SVM) and K-Nearest Neighbors (KNN) techniques are used to classify many human activities such as

(I) going down an incline, **(II)** going up an incline

(III) walking on level ground **(IV)** going down stairs,
(V) going up stairs
based on these steps: **(I)** strides detection **(II)** gait classification.

In [10], by using machine learning models such as SVM, ANN, Logistic Regression and Decision Tree which are widely used for many purposes such as physical and mental health monitoring and then the best set of parameters are selected using grid search. The dataset used was from UCI Machine Learning Repository as a standard dataset to train and test the models. Finally, the average accuracy was 96.33% using SVM.
In [8], multivariate data was chosen and various machine classification techniques Random Forest, KNN, Neural Network, Logistic Regression, Stochastic Gradient Descent and Naïve Bayes to analyze the human activity. Besides building AI models, confusion matrix was made for each model and Neural Network and logistic regression provides better accuracy for human activity recognition compared to other classifiers.

In [9], convolutional layers are combined with long short-term memory (LSTM), along with the deep learning neural network for human activities recognition (HAR). The dataset for a smartphone is used to collect data (various Human activities), the CNN model is applied, and each input image's output is transferred to the LSTM classifier as a time step. CNN-LSTM, as a proposed model has shown better activity detection capability than traditional algorithms with accuracy of 97.89%
According to previous works, we focused on two aspects (i) strides detection (ii) Human Activity classification. First, we followed some steps which are: (I) Filtration. (II) Smoothing. (III) Segmentation. (IV) Feature Extraction. (V) classify Human activities via machine learning algorithms which mentioned in [1] such as Naïve Bayes, Decision Tree, SVM and KNN.

3. Methods

The proposed method for recognizing human activities is presented in Figure 1 and detailed below. The method is divided into four stages: (I) Preprocessing (II) segmentation of data with window size (III) features extraction (IV) human activities classification.

Data acquisition is detailed in Section 3.1. Once the data has been collected, the acceleration signals are preprocessed and segmented (see Section 3.2). Finally, descriptive features are extracted from signals to classify the human activities, as it is detailed in Section 3.3.

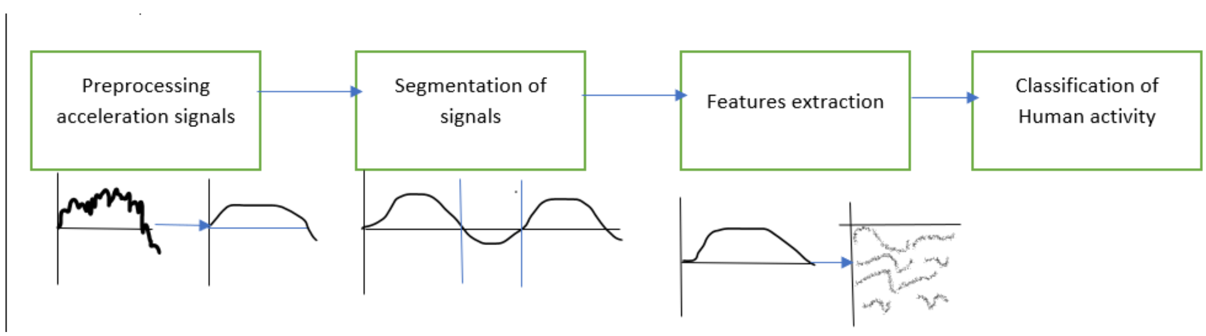

Figure 1. Proposed human activity recognition method

3.1. *Data Acquisition:*

Depending on accelerometer sensor in smart phones, we create a flutter application that acquiring acceleration data.

Five test subjects (21-22 years) carry smartphones in their right pocket where top of the smartphone is in the bottom of pocket and smartphone's screen faced their bodies during the capture sessions.

The human activities to be performed were: **(I)** Walking, **(II)** Going downstairs, **(III)** Going upstairs, **(IV)** Standing, **(V)** Sitting. The test was performed around NNN times at speed comfortable. The environments to carry out the activities were mixed between indoors and outdoors.

3.2. Preprocessing

At this stage acceleration signals are captured during the test then it has been processed through two techniques: **(I)** Filtration, **(II)**Smoothing

Filtration techniques depends on low-pass filter that applied to the acceleration signals x, y, z, using the coefficient a which filters the highest frequencies, the value of a was manually selected at 0.05. The purpose pf the filter to avoid artifacts due to movement and to decrease noise in acceleration signals.

Gaussian smoothing function is applied to filtered signals through using of gaussian_filter1d function from SciPy library. By giving gaussian_filter1d function acceleration data x, y, z, then sigma value to get smoothed data

Algorithm 1: Filter

Inputs: time-series three axes: $\{x, y, z\}$. a : filter coefficient.

Output: smoothed signals.

Start

```
Preprocessing acceleration signals:
  Fn Filter (signals):
        Set coefficient of filter (a),
        Set values of signals into list (S),
        Set empty list (X)
        For i←0:Size(S) do
              If i==0:
                    Append (a*S[i]) in list X
              Else:
                    Append ((1-a) * X[i-1] +a * S[i]) in list X
    Return List X.
```

3.3. Signal Segmentation

As Classification algorithm cannot directly applied to the raw time-series data. Using of Windowing techniques in which dividing data into windows of 100 second and then generating new feature by aggregating new sample contained within 50 seconds. for assigning label against the transformed feature, we take the most frequent activity in the window.

Algorithm 2: Windowing techniques

Start

Declare lists x_list, y_list, z_list, label_list

Set window size

Set step size

For i←0 in Size(length of rows in data – window size) with step size:

X=values of x acceleration signal

Y=values of Y acceleration signal

Z=values of Z acceleration signal

Label= from label select mode value

Append X in x_list

Append Y in y_list

Append Z in z_list

Append Label in label_list

End

3.4. *Feature Extraction*

For each window results from Section 3.2. Feature Extraction applied to extract about 18 Features:

- **I.** mean
- **II.** standard deviation
- **III.** average absolute deviation
- **IV.** minimum value
- **V.** maximum value
- **VI.** difference of maximum and minimum values
- **VII.** median
- **VIII.** median absolute deviation
- **IX.** interquartile range
- **X.** negative values count
- **XI.** positive values count
- **XII.** number of values above mean
- **XIII.** number of peaks
- **XIV.** skewness
- **XV.** kurtosis
- **XVI.** energy
- **XVII.** average resultant acceleration
- **XVIII.** signal magnitude area

3.5. Classification

Finally, in this section the features extracted are used to build human activity classifiers. Six algorithms were selected which are **(I)** Support Vector Machines (SVM), **(II)** Random Forest, **(III)** Decision Tree, **(IV)** K-Nearest Neighbors (KNN), **(V)** Naive Bayes (NB) **(VI)** Convolutional Neural Network (CNN).

1. Results

In order to evaluate the Human Activities Recognition model, our model passes through five stages which are: **-**

1. Human Activities Data acquisition.
2. Preprocessing: **-**
   - ➔ Filtration.
   - ➔ Smoothing.
3. Signal Segmentation.
4. Features Extraction.
5. Classification with some techniques:
   - ➔ Support Vector Machine.
   - ➔ K-Nearest Neighbors.
   - ➔ Random Forest.
   - ➔ Decision Tree.
   - ➔ Naive Bayes.
   - ➔ CNN

So, passing through all these stages helped us to improve our model's classification accuracies as they are shown in **Table [5]**.

Table 5: The Accuracy of dependent and independent for each algorithm used to classify Human Activities.

Technique Used	Accuracy of Dependent data	Accuracy of Independent Data
Support vector machine	0.86	0.65
K-Nearest Neighbors	0.87	0.56
Random forest	0.9	0.66
Decision Tree	0.87	0.66
Naive Bayes	0.72	0.61
CNN	0.84	0.68

4. Discussion

Human activity recognition systems might be implemented using more than one approach such as using images, videos, or acceleration data. Using acceleration data might be the best and easiest way to implement this kind of systems, because acceleration data is available in many devices used in our day-to-day life such as smartphones, smartwatches, and even it can be collected using a specially made devices for the sake of collecting this kind of data. That's why we have decided to use acceleration data for this project.

We also had to decide which Machine learning and Deep learning algorithms we will use in the Comparison process, so, we have decided to use five Machine learning algorithms which are SVM, Decision Tree, Random Forest, Naïve Bayes, K-Nearest Neighbors and for the Deep learning we chose the CNN Algorithm.

For the Machine learning algorithms, after the phase of collecting the data we come into the preprocessing, feature extraction, and segmentation phases which we had some difficulties while going through them. One of these difficulties was that the acceleration sensors is so sensitive and the sensitivity of each sensor might differ from one device to the other. So, we had to use smoothing functions to make the data kind of similar. Then we started the feature extraction phase to prepare the data which is going to be inserted into our classification model.

We also faced some problems in the segmentation phase because we didn't know which approach we should use to segment the data we had acquired so we had to try many approaches to get the best results from our data.

We then started the classification phase using the machine learning algorithms we mentioned before to start recognizing the human activity.

On the other hand, for the deep learning approach we didn't have to go through most of the phases we gone through in the machine learning approach.

The result we got from our machine learning, and Deep learning-based classification models were discussed in the results section in **Table [5]**. We have observed that the results of the classification models increased when we increased the size of the data acquired from the acceleration sensor.

Finally, we can increase the accuracy of the models by increase the quantity of the data acquired from the accelerometer, trying more segmentation methods to correctly identify each step in each activity.

5. Conclusions

Human activity recognition has many applications in medical research and human survey system. in this study, recognition of human activities: walking, standing, sitting, going upstairs, going downstairs was proposed based on acceleration data that has been collected by smartphones which is widely used by population where the smartphone placement was in the pocket.

This method of detecting activities used filtration, smoothing as preprocessing for acceleration data to decrease noise. Then segmentation using windowing techniques to extract 18 features of every activity. the features data were trained and tested using 6 learning methods: support vector machine, naive bayes, k-nearest neighbors, random forest, decision trees, and CNN.

In general, when we used dependent data and tested our machine learning models, we conclude that Random Forest scores the highest accuracy with 90% and the lowest one was Naive Bayes with 72% but CNN was not the best. But when we used an independent data and tested our machine leaning models, the voting classifier model was the best with 67% but CNN was better than all of machine learning models with 68%.

So, it is clear in our system that machine learning is better than deep learning when dependent data is used but with independent data, deep learning is the best.

The best classification accuracy rate in our project was 90% which is achieved by Random Forest, the results obtained in this study are promising. This work is in development and the lessons learned will be used to achieve more test results.

Abbreviations

The following abbreviations are used in this manuscript:

KNN	K-Nearest Neighbors
NB	Naive Bayes
SVM	Support Vector Machines
TNR	True Negative Rate
TPR	True Positive Rate

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