An Analytic Study on Human Activity Recognition using Smartphones

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Abstract – *The invention and advancement of a smartphone have proven to be a boon to the current and building future generations. With this immensely developing technology, one can achieve greater goals by managing everything merely on fingertips.*
Human Activity Recognition (HAR) is the need of the hour as it is an emerging study in the field of Medical Science and Automation. In today's fast-paced world, people hardly get any time to keep a check on their dependent near ones, this is where the HAR system comes into existence. A tool to keep an observation even without human intervention.
This project focuses on building a Human Activity Recognition System where data is collected, analyzed, modeled, and predicted into creating an Accurate System for human activity detection.
In this paper, we propose an approach of activity detection by choosing 30 people referred to as subjects carrying a waist-mounted smartphone embedded with inertial sensors (namely Accelerometer and Gyroscope). The human activities targeted in this system are walking, walking upstairs, walking downstairs, sitting, standing, and laying.
This study revolves around Machine Learning methodologies and techniques, precisely an approach based on semantic analysis mimicking the human ability to perform various activities.

Key Words: Human Activity Recognition, Smartphones, Machine Learning, Classification, Accelerometer, Gyroscope.

1.INTRODUCTION

With the increasing number of Smartphone Users worldwide, the HAR system finds its way to be a part and parcel of our lives. According to the statistical results provided by Statista, out of the 7.8 billion population, 3.8 billion population are smartphone users, which makes HAR an important field of study. This study uses the smartphone as a wearable device as it is one of the cheapest, most available and most owned wearable device.
The section below provides an introduction to all the concepts used in the project.

1.1 Smartphone Sensors

This project uses two Motion Sensors, that are commonly used in most of the Smartphones today – Accelerometer and Gyroscope. Using these sensors Smartphone processors understand the orientation of the phone in 3D space, helping with detection of human activity as the Smartphones are mounted on the waist of the subjects. The following section contains a brief detail of the working of these sensors and their contribution to the project.

Accelerometer: The accelerometer sensor measures the acceleration of gravity, determining the orientational changes from landscape to portrait, put simply vertical to horizontal. It is a technology introduced in all touch devices, measuring the acceleration force applied on all the 3-dimensional axial directions (x, y and z), including the force of gravity.

Gyroscope: This sensor measures the rotation and angular velocity of the device, adding an additional dimension to the information obtained from the accelerometer. It uses an advanced technology, measuring the angle at which the phone is placed/held.

Accelerator and Gyroscope
(with their directional axis)

Fig -1: Axial Direction of the Accelerometer and Gyroscope

In activity recognition, the accelerometer measures the linear speed while movement takes place, while a gyroscope measures the angular velocity speed. The detailed directional axial view of these sensors is depicted in Figure 1.

1.2 HAR Dataset

The smartphone dataset consists of recordings of 30 volunteers (referred to as subjects in this study), belonging to the age bracket of 19-48 years, performing daily human activities, that were captured through inertial sensors enabled device-smartphones. The smartphones were affixed to their waists and the data was recorded with the help of the motion sensors in the smartphone. The experiment was prerecorded to label the data manually.

Using the smartphones embedded accelerometer and gyroscope, we captured 3-axial linear acceleration (*tAcc-*

XYZ) from the accelerometer and 3-axial angular velocity (*tGyro-XYZ*) at a constant rate of 50Hz, with several variations. The prefix 't' in those metrics denotes time and the suffix 'XYZ' represents 3-axial signals in X, Y, and Z directions. These sensor signals are preprocessed by applying noise filters and then sampled in fixed-width windows (sliding windows) of 2.56 seconds each with 50% overlap. i.e., each window has 128 readings. From Each window, a feature vector was obtained by calculating variables from the time and frequency domain. In our dataset, each datapoint represents a window with different readings We get a feature vector of 561 features and these features are given in the dataset. Each window of readings is a datapoint of 561 features.[2] The obtained dataset has been randomly partitioned into two different sets, where 70% of the volunteers were selected for generating the training data and the rest 30% the test data.

This project is focused onto building a classification model that can precisely identify human activities like walking, walking upstairs, walking downstairs, sitting, standing, and laying. This machine learning project also gives a brief understanding on solving a multiclass classification problem.

2. Methodology

The Human Activity Recognition (HAR) system studied through this paper is an example of Supervised Learning. Supervised Learning is a Machine Learning task which learns a function that maps an input to an output based on example input-output pairs. Classification is a division of supervised learning. It specifies the belonging class of the data elements and is best used when the output values are finite and discrete. It also predicts a class for an input variable. The following sub sections give a detailed explanation of the different phases of the project.

2.1 Exploratory Data Analysis

1. Feature Mapping

From each sampled window described above a vector of features was obtained. Standard measures previously used in HAR literature [3] such as the mean, correlation, signal magnitude area (SMA) and autoregression coefficients [4] were employed for the feature mapping. A new set of features was also employed in order to improve the learning performance, including energy of different frequency bands, frequency skewness, and angle between vectors (e.g. mean body acceleration and y vector).

Table 1 contains the list of all the measures applied to the time and frequency domain signals. A total of 561 features were extracted to describe each activity window. In order to ease the performance assessment, the dataset has been also randomly partitioned into two independent sets, where 70% of the data were selected for training and the remaining 30% for testing. The Human Activity Recognition dataset has been made available for public use and it is presented as raw inertial sensors signals and also as feature vectors for each pattern. It has been submitted as the Human Activity Recognition using Smartphones dataset in the UCI Machine Learning Repository [5] and can be accessed following this link (information concerning the licensing and usage of the data can be retrieved in the readme file included): archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones [2]

Table 1: List of measures for computing feature vectors.

Feature Vectors	
Function	**Description**
mean	Mean value
std	Standard deviation
mad	Median absolute value
max	Largest values in array
min	Smallest value in array
sma	Signal magnitude area
energy	Average sum of the squares
iqr	Interquartile range
entropy	Signal Entropy
arCoeff	Autorregresion coefficients
correlation	Correlation coefficient
maxFreqInd	Largest frequency component
meanFreq	Frequency signal weighted average
skewness	Frequency signal Skewness
kurtosis	Frequency signal Kurtosis
energyBand	Energy of a frequency interval
angle	Angle between two vectors

2. Feature Engineering

Feature Engineering is the process of using domain knowledge for transforming the raw data collected into different features that represent the underlying problem to the predictive models, resulting in improved predicted model accuracy on unseen data. Feature engineering is an art which is all about creating new input features from your existing ones.

In figure 2, the dataset consisting of six activities were sorted based on the feature -Static and Dynamic activities. According to this feature applied, we observe that in static activities (sit, stand, lie down) motion information is of least importance, whereas in the dynamic activities (Walking, Walking Upstairs, Walking Downstairs) motion information will be significant.

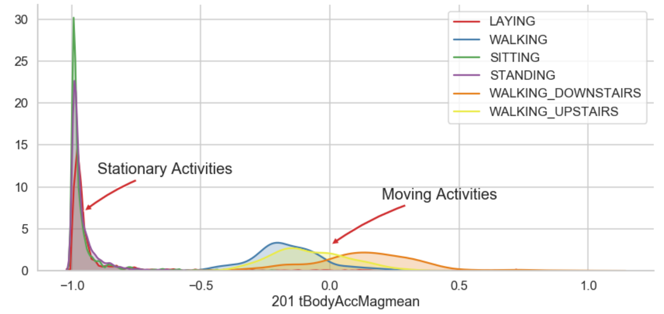

Fig -2: Classification of Static and Dynamic movements

The figure 2 shows a clear representation of the separation of dynamic and static activities (Moving and Stationary activities).

3. Feature Selection

Feature Selection is one of the most important core concepts in machine learning which hugely impacts the performance of your model. The data features that are used to train the machine learning models have a huge influence on the performance that can be achieved. Irrelevant or partially relevant features can negatively impact model performance. Let us get a brief idea of this concept by explaining a few features of this project.

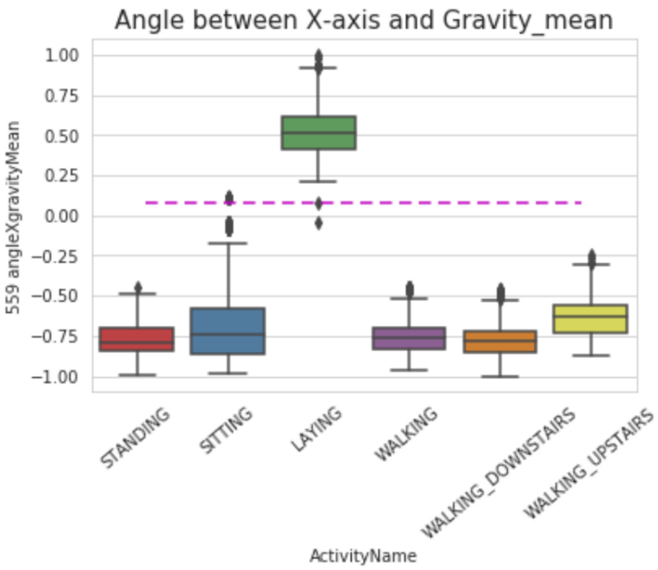

Fig -3: Feature selection (559) for activity separation

The figure 3 represents that Position of Gravity acceleration components can also be used as a distinguishing feature, categorizing the data on a particular feature name – 559 angleXgravityMean. This feature brings about a separation between the Laying activity and the rest of the activities. As we can observe, this feature creates a relation with the angle between the X-axis and the Gravity_mean, which logically states that while laying the position of the smartphone would be perpendicular with respect to the ground. We conclude that if f angleX,gravityMean > 0 then Activity is Laying.

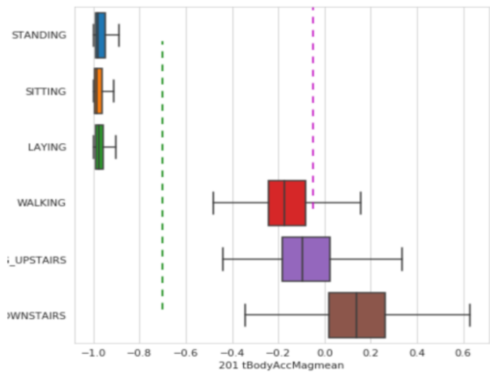

Fig -4: Feature selection (201) for activity separation

Figure 4 depicts a classification of the activities based on the feature name – 201 tBodyAccMagmean. This feature implies that the magnitude of acceleration can separate the activities properly, therefore making conclusions from the figure that:
If tAccMean is < -0.8 then the activities are either standing, sitting or laying.
If tAccMean is > -0.6 then the activities are either walking or walking_downstairs or walking_upstairs.
If tAccMean > 0.0 then the Activity is walkingDownstairs.
We can classify 75% the Acitivity labels with least errors.

Feature engineering helps bring about such distinguishing features amongst the data, that helps in studying the data and exploring it in depth.

4. t- SNE Plot

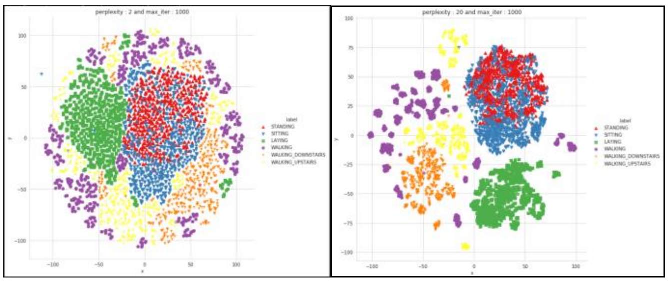

Fig -5: t-SNE plot used for separation of activities

t-Distributed Stochastic Neighbor Embedding (t-SNE) is a technique for dimensionality reduction particularly suited for the visualization of high-dimensional datasets. The figure 5 shows the comparison between the activity data with different perplexity values. As we can observe, initially with perplexity = 2, the data is randomly scattered, no proper partition is visible. With the increase in perplexity (perplexity = 20), the different types of activity data forms clusters, except for standing and sitting.

2.2 Machine Learning Models

The following are the Machine Learning Models used in this HAR System.

Table -2: Machine Learning Models

HAR Machine Learning Models		
ML Model	Training time	Accuracy
1. Logistic Regression	13.84 s	0.9589
2. Linear SVC	49.69 s	0.9674
3. RBF SVM Classifier	11.27.34 m	0.9626
4. Decision Tree	21.86 s	0.8764
5. Random Forest	08.03.71 m	0.9277
6. Gradient Boosting DT	07:59:00:11 h	0.9233

Based on the data provided in the above Table 2, we observe that the Models with high accuracy and less training time are the efficient prediction models for this project.

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                          Accuracy      Error
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Logistic Regression     : 95.89%        4.106%
Linear SVC              : 96.74%        3.258%
rbf SVM classifier      : 96.27%        3.733%
DecisionTree            : 87.65%        12.35%
Random Forest           : 92.77%        7.228%
GradientBoosting DT     : 92.77%        7.228%
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Fig -6: Final Prediction Table

In this HAR system, the following Models give us the highest accuracy percentage and so we can choose one amongst 1. Logistic Regression, 2. Linear SVC, 3. Rbf SVM Classifier, as the Final Prediction Models.
Let us study these models in detail. The figures in each of the sub sections below plot the Confusion matrix for each of these algorithms, depicting the accuracy as well as the error percentages.

1. Logistic Regression

Logistic Regression is a Machine Learning algorithm mostly used for classification problems, also a predictive analysis algorithm and based on the concept of probability. The target or dependent variable has a dual nature, which means it is binary having classes either 0 (success) or 1(failure). Mathematically, the logistic regression model predicts P(Y=1) as a function of X.

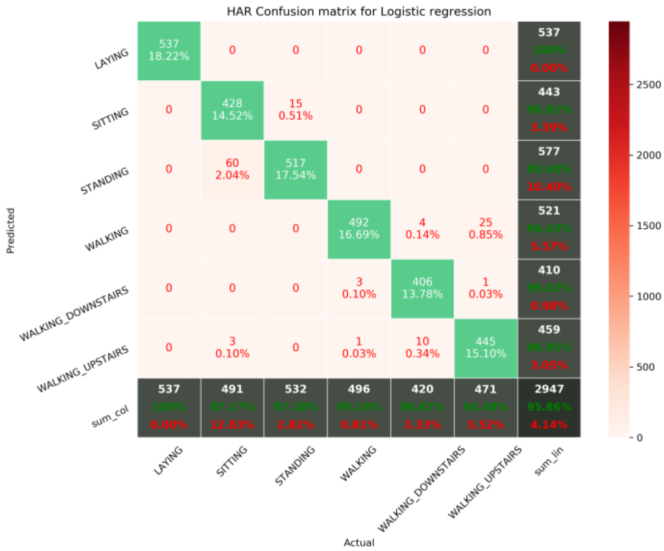

Fig -7: Logistic Regression Confusion Matrix

2. Linear SVC

The objective of a Linear SVC (Support Vector Classifier) is to fit to the data you provide, returning a "best fit" hyperplane that divides, or categorizes, your data. From there, after getting the hyperplane, you can then feed some features to your classifier to see what the "predicted" class is. [6]

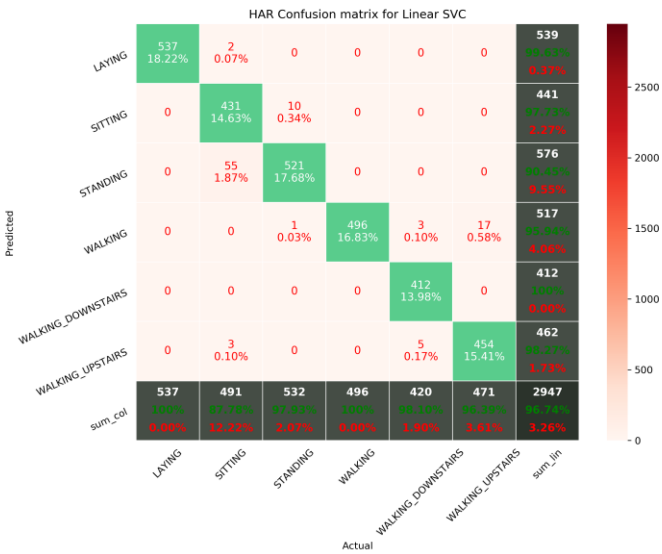

Fig -8: Linear SVC Confusion Matrix

3. RBF SVM Classifier

The Radial basis function kernel, also known RBF kernel, or Gaussian kernel, is a kernel that is in the form of a radial basis function.

It is a general-purpose kernel; used when there is no prior knowledge about the data.[7]
Equation is:

$$k(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\gamma \|\mathbf{x_i} - \mathbf{x_j}\|^2)$$

Gaussian radial basis function (RBF)

, for:

$$\gamma > 0$$

Gaussian radial basis function (RBF)

Sometimes parametrized using:

$$\gamma = 1/2\sigma^2$$

Gaussian radial basis function (RBF)

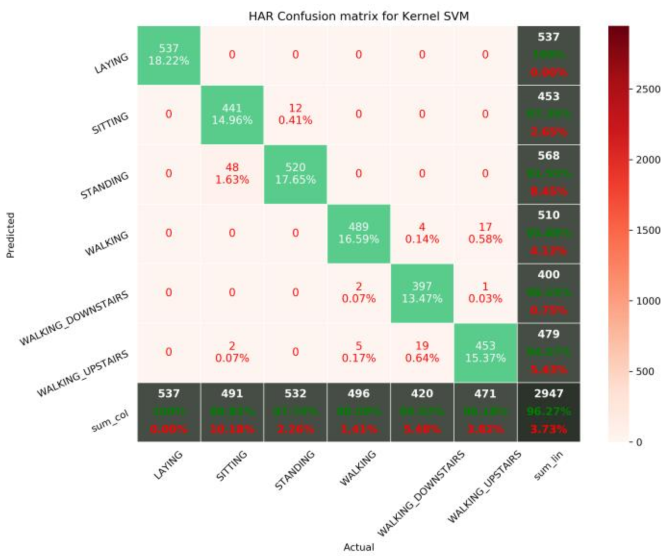

Fig -9: RBF SVM Classifier Confusion Matrix

3. CONCLUSIONS

In this paper, we have presented a Human Activity Recognition system which performs accurately using one of the multiclass classification models mentioned above. We got a recognition accuracy of up to 96.74% (highest) on the six everyday activities using the accelerometer and gyroscope signals.

The best classification rate in our experiment was 96.7%, which is achieved by Linear SVC. For future work, we look forward to extend our HAR system to be trained to 1. Be able to detect more activities, 2. Create a system based on User's age group, so that their activity patterns can be used to show similarity, and 3. Add more features and perform advanced feature engineering techniques for a better distinguished activity system.[8] We would also like to implement a real - time system on a smartphone which can be used for real time activity detection.

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