A Capstone Project for Machine Learning Nanodegree at Udacity

by Glenn Mossy December 25, 2019 (Latest)

https://github.com/gmossy/human-activity-recognition

1 Definition

1.1 Project Overview

The goal of activity recognition is to recognize common human activities in real life settings. Human activity recognition or HAR for short is the problem of predicting what a person is doing based on a trace of their movement while doing a specific activity using sensors. This is a classification project, since the variable to be predicted is categorical. HAR plays an important role in people's daily life for its competence in learning profound high-level knowledge about human activity from raw sensor inputs.

Human Activity Recognition is appealing in applications ranging from security-related applications, logistics support, location-based services and exploitation of Ambient Intelligence by helping handicapped or elderly people to live more independently, rate health levels for healthcare, activate household controls, appliances and provide safety by monitoring. HAR is very multifaceted, useful many fields and may also be referred to as goal recognition, behavior recognition, location estimation, monitoring etc. With knowledge from the models, results can be used to perform Ambient Assisted Living. Using better capability to predict human behavior means we can proactively deliver specialized programs and targeted interventions to the populations that are most in need.

Human Activity Recognition aims to identify the actions carried out by a person during a set of observations from the person's movements and surrounding environment, and then ultimately used to build and use models for a wide range of human activities. Recognition can be accomplished by exploiting the information retrieved from various sources such as body-worn sensors. It is believed that by empowering a computer to monitor the behavior of agents, computers can become and suited to act on our behalf.

This project explores a readily available dataset from the UCI [1] that is based on the work "Human Activity Recognition on Smartphones with Awareness of Basic Activities and Postural Transitions", by Jorge-Luis Reyes-Ortiz, Luca Oneto, Alessandro Ghio, Albert SamÃ¡, Davide Anguita and Xavier Parra. This work expands on their earlier work done [2] "A Public Domain Dataset for Human Activity Recognition Using Smartphones." by adding a study of Postural Transitions. In this project I build several machine learning models to train and predict the human activities such as walking, walking upstairs, walking downstairs, sitting, standing, or laying along with postural transitions from one of standing, sitting or lying positions to their opposites. Accuracy scoring and analysis will be done on the performance of each of the models. One of the challenges with this dataset it will be an unbalanced dataset, with the postural activities do not have as many datapoints as the other activities.

The project in which this paper is based [1] uses sensors that are body mounted accelerometer and gyroscope but many additional sensors, such as microphones, motion video capture, human physiological signals or vital signs could be later added to this project in order to capture data to provide additional features to the model that would improve the accuracy, provide more data for the models, and increase the number of activities that can be recognized, with the ultimate goal of providing a real-time prediction of each and every activity that the person is doing.

My interest in this field stems from participation in AT&T Software Symposium Hackathons in which my team came in second place in 2018 by creating a project to provide assisted living support to wheelchair bound, severely disabled patients. In my part-time work as adjunct instructor at Frederick Community College I teach students how to program Arduino microcontrollers and sensors to interact with the physical environment. In my full-time position I'm am with AT&T Public sector where I am a Senior Solutions Architect providing technical leadership on Technology Innovation initiatives for our Nations Department of Defense, DISA, Army and Cyber programs. In this role I support multi-vendor, high risk/reward integration projects, including rapid software development, enterprise networking and automation that enables business processes, and provides operations automation.

1.2 Problem Statement

Human Activity Recognition or HAR for short, is the problem of predicting what a person is doing based on a time series recording of their movement using sensors. The idea is that once the subject's activity is recognized and known, it can be saved in a model that can then be used to recognize future those activities with high accuracy when applied, and then provide useful assistance with the result.

The objective is to build a classifier that can classify the different activity types, even when extended to new data (i.e.: new participants).

Movements that we will study in this project will be six normal indoor activities such as walking, standing, sitting, laying and walking up and downstairs, also six postural transitional activities will be included these are moving from standing to sit, or laying down to sit, or laying to standing. By using sensors in a smartphone, 3-axial linear acceleration from an accelerometer and 3-axis angular velocity from gyroscope data in three dimensions (x, y, z) is recorded.

It is a challenging problem because there is no clear analytical way to relate the sensor data to specific actions in a general way. It is technically challenging because of the large volume of sensor data collected (e.g. tens or hundreds of observations per second) and the classical use of hand-crafted features and heuristics from this data in developing predictive models.

In this project, we will examine data that will be an unbalanced data set, with the normal activities will have more data points than the postural activities, refer to table 1 for a list of the activities. Using confusion matrixes, and scoring that calculates precision, recall, f1, and accuracy scores, and r2, and the Matthews correlation coefficient for each model, evaluate and discuss the accuracy of how each of the models perform. It will also be noted how long it takes to train the models, which can provide insight on models that can be used in near real-time to learn new activities.

Classical approaches to the problem involve training machine learning models, such as ensembles of logistic regression or random forest methods, while in this project, the objective is build machine learning models to classify activities into one of the twelve activities performed and then score and analyze the results, and special models to evaluate if is there is improvement, using a stacking model and a basic artificial neural network model to see how well they do.

1.3 Metrics

The objective of this project is to predict the activity performed by the subject accurately, based on accelerometer and gyroscope readings, so misclassification rate is chosen with several assessment measures to compare the performance of different models. With the dataset ready, the HAR problem essentially becomes a classification problem with labeled data under supervised learning. This project addresses the HAR problem by applying different types of machine learning techniques: supervised learning using several classifiers (e.g. Logistic Regression, AdaboostClassifier, GradientBoostClassifier, K nearest Neighbors, Random Forest Classifier, Linear Support Vector Machines, and Stacking (a set of the classifiers, which creates a meta-classifier). And finally, a basic Artificial Neural Network (ANN) is used to corroborate the results from the other classifiers. For each of the proposed algorithms, accuracy and a set of metrics are used as the common metrics to compare performances.

The classification Accuracy is what we usually mean when we use the term accuracy. It is the ratio of number of correct predictions to the total number of activity input samples. We will record the training and the testing accuracy. The training accuracy tells us how well the training was performed on the training samples, while the testing accuracy tells us the ratio of number of correct predictions to the total number of activity input test samples. Most of the time we use classification accuracy to measure the performance of our model, however it is not enough to truly judge our model. Accuracy score coupled with a confusion matrix give a more robust assessment of the model performances. We will also examine in the LR classification and ANN model, the zero one loss, and the max_error.

There are five other metrics that will be used to measure performance of the models, the confusion matrix, the Precision-Recall scores, F1 Score (weighted ave and macro ave), the R2 score, and the Matthews correlation coefficient. Additionally, we will record the training time to compare how fast the model performance is for training.

The confusion matrix, which is an output table that summarizes the number of true positives, true negatives, false positives, and false negatives, and describes the complete performance of the model. The confusion matrix is a straightforward evaluation metric if we assume that the results have balanced classes, in the number of true positives to true negatives. A confusion matrix is particularly helpful to evaluate the models used. Specifically, precision represents the number of correctly classified activities out of all the activities being classified. [11] In our case, we do have an imbalanced dataset.

So, the Precision-Recall evaluation metrics can be used if we find that the dataset is imbalanced. Precision represents the number of correctly classified activities out of all the activities being classified; while recall represents each type of activity in truth how many the machine correctly classified. Precision is the number of true positives over the number of total positive predictions. A

high precision means that there will be many true positives and a low false positive rate. Recall is the number of true positives over the number of total actual positives in the dataset. A high recall means that the model has captured most of the true positives and has a low false negative rate. An optimal solution needs to have high precision and high recall, rejecting only those activities that don't match the class, i.e. high precision, and matching the correct activity to the class in the dataset (high recall).

F1 Score is the Harmonic Mean between precision and recall. The range for F1 Score is [0, 1]. It tells you how precise the classifier is (how many instances it classifies correctly), as well as how robust it is (it does not miss a significant number of instances).

The r2_score function computes the coefficient of determination, usually denoted as R^2. . It represents the proportion of variance (of y) that has been explained by the independent variables in the model. It provides an indication of goodness of fit and therefore a measure of how well unseen samples are likely to be predicted by the model, through the proportion of explained variance. As such variance is dataset dependent, R^2 may not be meaningfully comparable across different datasets. The best possible R2 score is 1.0 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

The Matthews Correlation Coefficient (MCC) has a range of -1 to 1 where -1 indicates a completely wrong binary classifier while 1 indicates a completely correct binary classifier. Using the MCC allows one to gauge how well their classification model/function is performing. The Matthews correlation coefficient is used in machine learning as a measure of the quality of binary (two-class) classifications. It considers true and false positives and negatives and is generally regarded as a balanced measure which can be used even if the classes are of very different sizes.

We will look at what the R2 score and Matthews correlation coefficient tells us about the performance of the test data. Depending on the imbalance of the data, the mcc may or may not be a more positive result, while the R2 score which is a statistical measure will tell us how close the data are to the fitted regression line.

2 Analysis

2.1 Data Exploration

A standard human activity recognition dataset is the 'UCI [1] that is based on the work "Human Activity Recognition on Smartphones with Awareness of Basic Activities and Postural Transitions" that was made available in 2014. It was prepared and made available by Jorge-Luis Reyes-Ortiz, et al. from the University of Genova, Italy and is described in full in their 2014 paper. The dataset was made available and can be downloaded for free from the UCI Machine Learning Repository. The README.MD file in this project describes how to obtain and use the dataset. Here is a summary of the dataset files in Table 1, in addition, the original source dataset includes the raw data that was not used in this project, but can be used by the reader to expand on this work to manipulate the data based to improve on the work in this project.

Table 1 Summary of the components of the Dataset Used

X_train	The shape of the training set dataframe is (7767, 561) Figure 2 is an example
y_train	The shape of the training set labels dataframe is (7767, 1) Figure 3 is an example
X_test	The shape of the testing set dataframe is (3162, 561)
y_test	The shape of the test set labels dataframe is (3162, 1)
Activity_labels	Links the class labels with their activity name. See Table 2 for a list.
subject_train	Each row identifies the subject who performed the activity for each window sample.
subject_test	Each row identifies the subject who performed the activity for each window sample.
features	List of all features, See Table 3 for a list of the feature signal types.

The data was collected from 30 subjects aged between 19 and 48 years old performing 12 standard activities while wearing a waist-mounted smartphone that recorded the movement data. The movement data recorded was the x, y, and z accelerometer data (linear acceleration) and gyroscopic data (angular velocity) from a smartphone, specifically a Samsung Galaxy S II. Video was also recorded of each subject performing the activities and the movement data was labeled manually from these videos and can be used for reference to see how the activities were recorded. [x]. The HAR dataset was collected in laboratory conditions but volunteers were asked to perform freely the sequence of activities for a more naturalistic dataset. The set of experiments in which each person was instructed to follow was a protocol of activities while wearing a waist-mounted Samsung Galaxy S II smartphone.

Each subject performed the sequence of activities twice; once with the device on their left-hand-side and once with the device on their right-hand side. After a series of preprocessing, the final dataset has 561-feature vector per example derived from 17 action patterns and 17 functions over 12 activities labels. So, the target variables have 12 different classes, the basic activities plus the postural activities as follows:

Table 2 The Activities and activity_labels

Standard Activities	0	WALKING	Moving
	1	WALKING_UPSTAIRS	
	2	WALKING_DOWNSTAIRS	
	3	SITTING	Stationary
	4	STANDING	
	5	LAYING	
Postural Activities	6	STAND_TO_SIT	Moving
	7	SIT_TO_STAND	
	8	SIT_TO_LIE	
	9	LIE_TO_SIT	
	10	STAND_TO_LIE	
	11	LIE_TO_STAND	

There is a datafile " subject_id_test.txt" that contains rows that identifies the subject who performed the activity for each window sample. Its range is from 1 to 30.

```
df=pd.DataFrame(subject_train)
df.T
```

	0	1	2	3	4	5	6	7	8	9	...	7757	7758	7759	7760	7761	7762	7763	7764	7765	7766
0	1	1	1	1	1	1	1	1	1	1	...	30	30	30	30	30	30	30	30	30	30

1 rows × 7767 columns

Figure 1 subject_train dataset example

Observations were recorded at 50 Hz (i.e. 50 data points per second), that was consistent across the dataset. The raw data is not available, but instead a pre-processed version of the dataset was made available. The dataset used in this project had already been pre-processed. In particular, the SBHAR data generated around 5-hours of experimental data, and was also pre-processed with noise filters Instead, The pre-processing steps included: Pre-processing accelerometer and gyroscope using noise filters and other data transformations were also applied including the calculation of Jerk signals from time, body linear acceleration and angular velocity information; magnitude using Euclidean norm and, the frequency domain signals using Fast Fourier Transform (FFT).

From this dataset we get a feature vector of 561 elements. The readings were split into training data (71.07%) and the remaining as testing data (28.93%) sets based on data for a total of 30 subjects, e.g. 21 subjects for train and nine for test. After checking for duplicates and null values, both datasets were found to be clean. The signal data points are captured on 3 axes and have been preprocessed and bounded between [-1,1].

The training dataset (X_train) has 7767 rows x 561 columns and the test dataset (X_test) has 3162 rows and 561 columns. Here's an example (only some of the 561 columns and 7767 rows) of what part of the training dataset looks like:

	tBodyAcc-Mean-1	tBodyAcc-Mean-2	tBodyAcc-Mean-3	tBodyAcc-STD-1	tBodyAcc-STD-2	tBodyAcc-STD-3	tBodyAcc-Mad-1	tBodyAcc-Mad-2	tBodyAcc-Mad-3	tBodyAcc-Max-1	...	fBodyGyroJerkMag-MeanFreq-1	fBodyGyroJerkM Skewne
0	0.043580	-0.005970	-0.035054	-0.995381	-0.988366	-0.937382	-0.995007	-0.988816	-0.953325	-0.794796	...	-0.012236	-0.31
1	0.039480	-0.002131	-0.029067	-0.998348	-0.982945	-0.971273	-0.998702	-0.983315	-0.974000	-0.802537	...	0.202804	-0.60
2	0.039978	-0.005153	-0.022651	-0.995482	-0.977314	-0.984760	-0.996415	-0.975835	-0.985973	-0.798477	...	0.440079	-0.40
3	0.039785	-0.011809	-0.028916	-0.996194	-0.988569	-0.993256	-0.996994	-0.988526	-0.993135	-0.798477	...	0.430891	-0.13
4	0.038758	-0.002289	-0.023863	-0.998241	-0.986774	-0.993115	-0.998216	-0.986479	-0.993825	-0.801982	...	0.137735	-0.36

5 rows × 561 columns

Figure 2 X_train data sample

The labeling dataset y_train and has 1 row and 7767 columns as shown below, and the y_test dataset has 3162 columns.

	0	1	2	3	4	5	6	7	8	9	...	7757	7758	7759	7760	7761	7762	7763	7764	7765	7766
Y	5	5	5	5	5	5	5	5	5	5	...	2	2	2	2	2	2	2	2	2	2

1 rows × 7767 columns

Figure 3 y_train dataset sample

The sensor signals are preprocessed by the authors of the original paper which involved 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. So, in our dataset, each datapoint represents a window with different readings. The acceleration signal was separated into body and Gravity acceleration components using a low pass filter with a corner frequency of 0.3Hz. After that the body linear acceleration and angular velocity were derived in time to obtain jerk signals. Then the magnitude of the 3-dimensional signals was calculated using the Euclidian norm. Finally, the frequency domain signals were obtained by applying an FFT (Fast Fourier Transform). These signals are labeled as fBodyAcc-XYZ, and fBodyGyroMag, etc. Finally from the base signal readings there are calculations provided for mean value, max (largest value in the array), sma (Small signal magnitude area), arCoefficient (Autoregression coefficients, and correlation() coefficients between signals, meanFreq, skewness, kurtosis, energy bands measure, signal entropy and a few others

The acceleration signal from the smartphone accelerometer X axis in standard gravity units 'g'. The body acceleration signal obtained by subtracting the gravity from the total acceleration. The angular velocity vectors were measured by the gyroscope for each window sample. The units are radians/second. The input variables include time and frequency domain signals obtained from the smartphone sensors:

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Table 1 feature input Inertial signals in the time and frequency domain

body_acceleration
gravity_acceleration
body_acceleration_jerk
body_angular_speed
body_angular_acceleration
body_acceleration_magnitude
gravity_acceleration_magnitude
body_acceleration_jerk_magnitude
body_angular_speed_magnitude
body_angular_acceleration_magnitude

An examination of the properties of the signal samples for the train dataset and the test dataset: Mean value, standard deviation, Quartile values, and Maximum values are close in range between the two datasets, so the test data is very similar to the training data.

Here is a list of the where to get the data and a list of the HAPT dataset files.

http://archive.ics.uci.edu/ml/machine-learning-databases/00341/

/HAPT Data Set/Train/subject_id_traintxt

/HAPT Data Set/Train/X_traintxt

/HAPT Data Set/Train/y_traintxt

/HAPT Data Set/activity_labels

/HAPT Data Set/features

/HAPT Data Set/activity_labels

/HAPT Data Set/features_info

2.1 Exploratory Visualization

The visualizations that were done include Number of Samples per Activity", “Samples of Activities provided by each Test Subject”, “Plots of 3 Axis Body Acceleration Mean Values with Respect to Frequency vs the Activity Type”, Visual exploration of the data in 3 dimensions with principal component analysis, and finally, “Visualization of Feature Distribution”. Below we explain why the visualization was chosen and how the chart is relevant to our analysis of the solution.

2.1.1 Number of Samples per Activity

Looking at the total samples count vs the 12 activities, we have an imbalance in the 12 classes of activities with the number of samples below 32 total datapoints each for the postural activities.

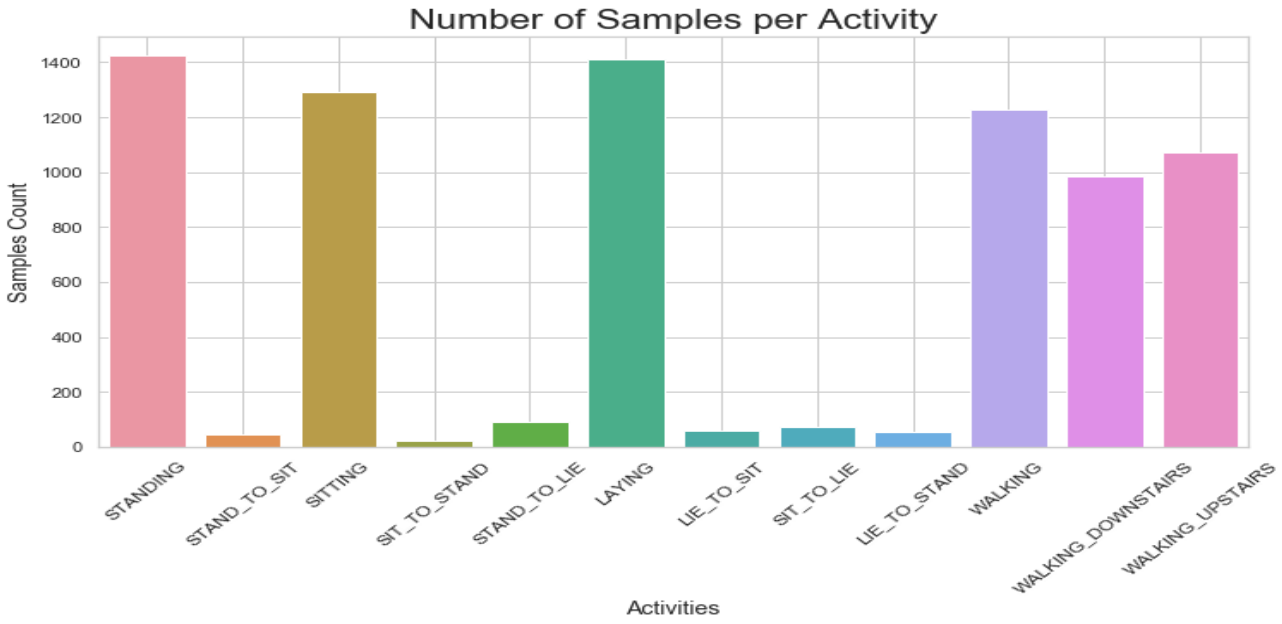


Figure 4 Number of Samples per Activity Chart

2.1.2 Samples of Activities provided by each Test Subject

All our test subject has performed the six normal activities between 37 and 85 samples. In future improvement samples could be taken more even between the subjects and would help balance out the test dataset. The six postural activities count is small, under 10 samples each subject, which is considerably lower than the normal activity samples. Increasing these samples closer to the count of the normal samples could significantly improve the outcome of our predictions. Below in Figure 5 is a Plot of Samples of Activities provided by each Test Subject.

Special note should be made of the “SIT_TO_STAND” count, which is the lowest of all, and ranges from activity ranges only from 0 to 10. This is not enough training data for proper analysis and prediction. Our results, as can be seen in the confusion matrixes, do poorly for this activity.

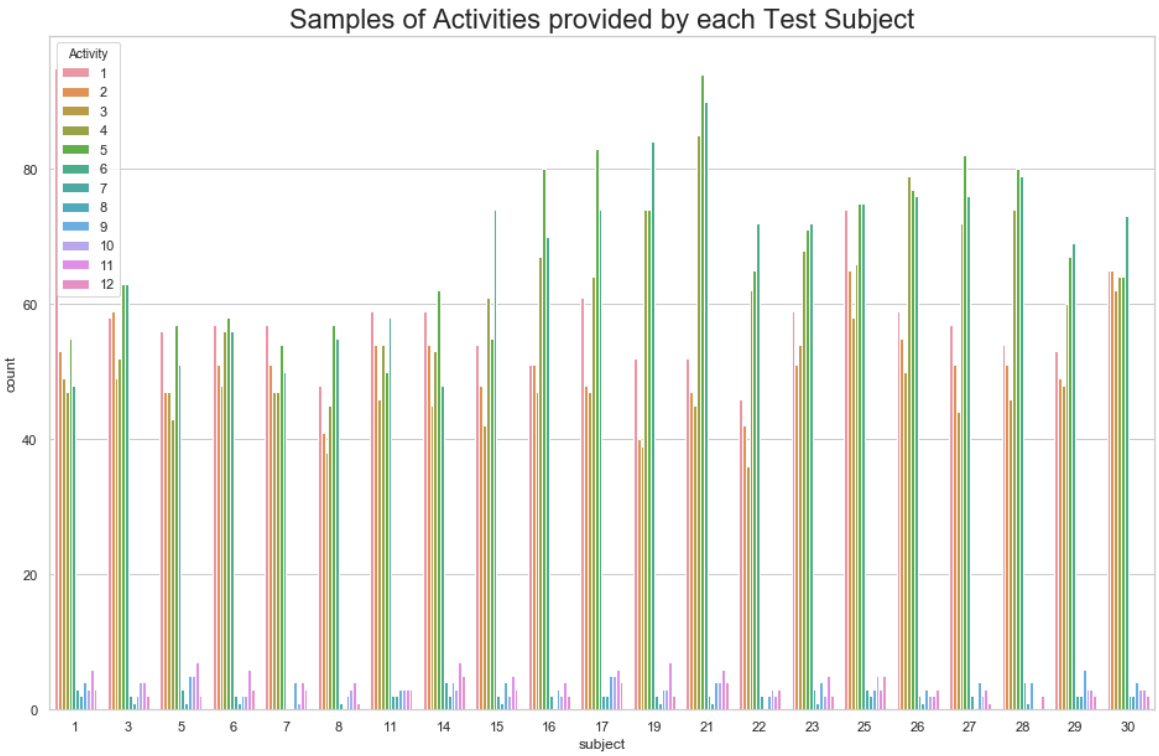


Figure 5 Samples of Activities provided by each Test Subject

2.1.3 Plots of 3 Axis Body Acceleration Mean Values with Respect to Frequency vs the Activity Type

Now we Plot the various features vs the activity type to examine the relationships visually and will note interesting observations. In the 3 Axis Body Acceleration plot, we identify there are three major groups of activities have the most similar frequency variations. The grouping can be seen as group 1, "walking, walking_upstairs, walking_downstairs, group 2, siting and standing, laying (these are the stationary activities we identified in the feature distribution visualization below, and group 3, the postural activities all are mostly similar. This means that we could possibly add some different scaling of the dataset value ranges to each of these 3 activity groups. This could reduce overfitting, if we then train the groups separately. For example, group 2 ranges from -1.0 to 0.0, the frequency plots have not ranged over 0.0. We could re-scale these types of activities together, whereas the other activities go above and below the 0.0 axis.

Special note should be made of the "SIT_TO_STAND" graph, because the signal has is missing to the right half of the graph. After reviewing the confusion matrix graphs, the true positives for this activity

ranges only from 0 to 10, and under 5 in most results. This lab capture should be redone.

Figure 6 Plots of 3 Axis Body Acceleration Mean Values with Respect to Frequency vs the Activity Type

2.1.4 Visual exploration of the data in 3 dimensions with principal component analysis

Using PCA chart show below, we can see 6 distinct color groupings within 3 main clusters - the 3 variations of walking are close together in the as one would expect. The static activities of Sitting/Standing/Laying are similarly close together, while the moving activities, Stand_to_Sit/Sit_to_Lie, etc are spread out across their associated components. In earlier work done [2] the authors did use these distinct six classes of activities of groupings. We will see how well we can still identify the activities, which are the postural activities, that are outliers from these six clusters. This identification could lend to redesigning the activities, for example standing_and_rotate instead of stand_to_lie, as that perhaps body turning rotation is an intermediate step when you transition from standing to laying down.

Special note can also be made of the “LAYING” graph, which looks to be abnormal for what should be a subject lying still in bed. However, the signal for it happens to be more unique than any of the others and may produce more true predictions.

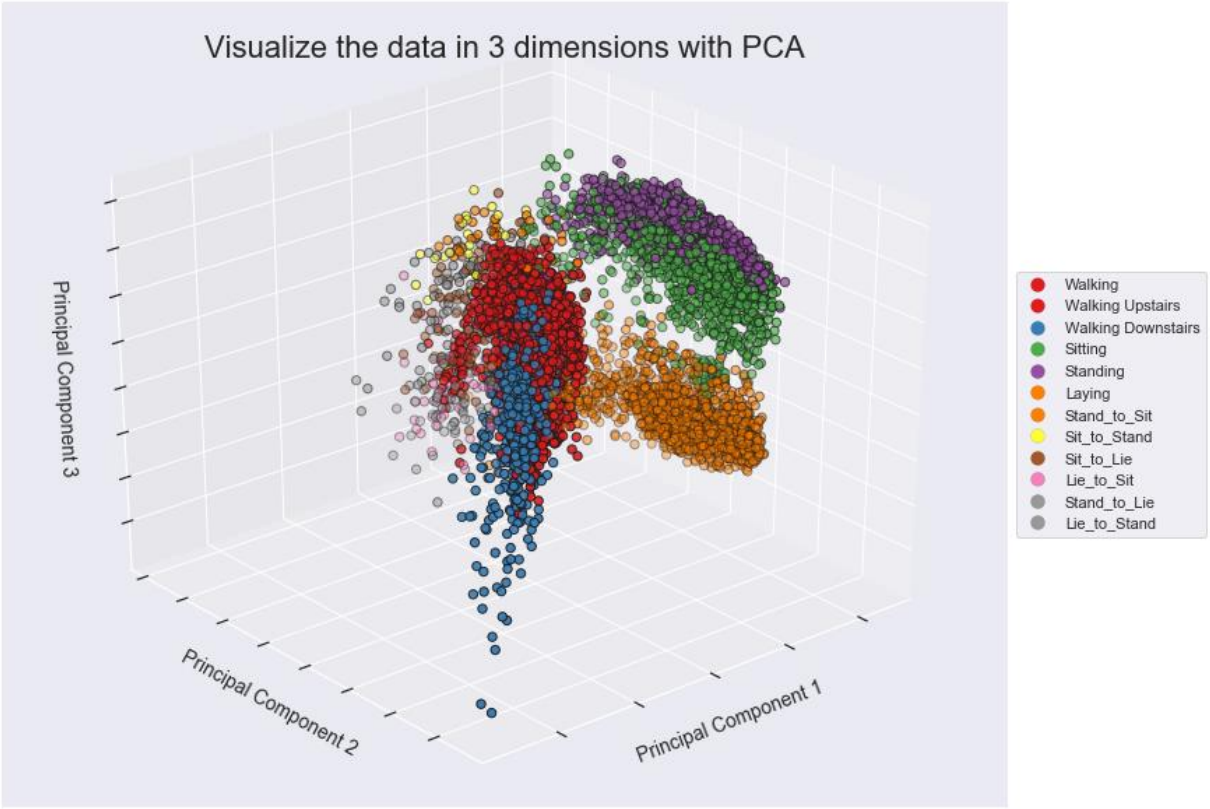
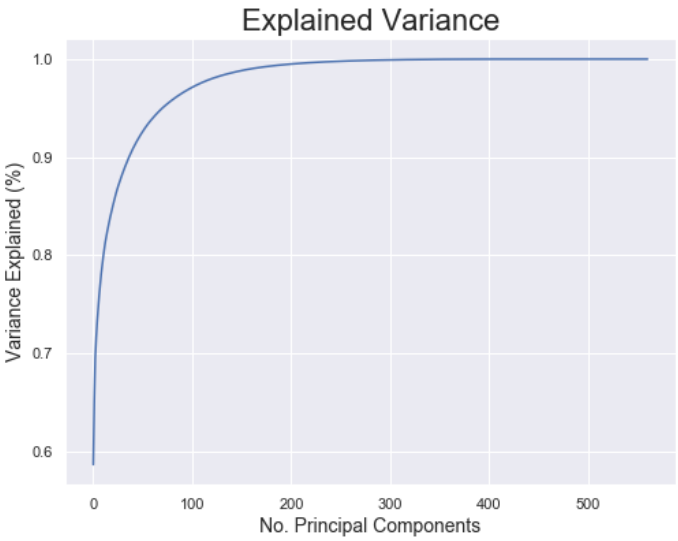


Figure 7 Principal Component Analysis Visualization in 3 dimensions



In this Plot PCA Explained Variance curve we evaluated if we need to use one set of components over the other, Using this Explained Variance Graph we can see about 100 components capture more than 95% of the variance in the X train data, while about 200 components capture nearly 100% of the variance in the training data. This variance is so close that in this project we will keep these components grouped together.

2.1.5 Visualization of Feature Distribution

In the following 3 charts, "Visualization of Feature Distribution plots", the features have been visualized to be certain of and identify which are the stationary, moving features and to look for anomalies. Three plots were required due to the number of features, 10 features per plot. If we have new features to engineer for example a new type of sensor, we need to be able to understand its properties. As an improvement to the models, the features that can be clustered can be separately modeled into a revised dataset into the model to prevent overfitting.

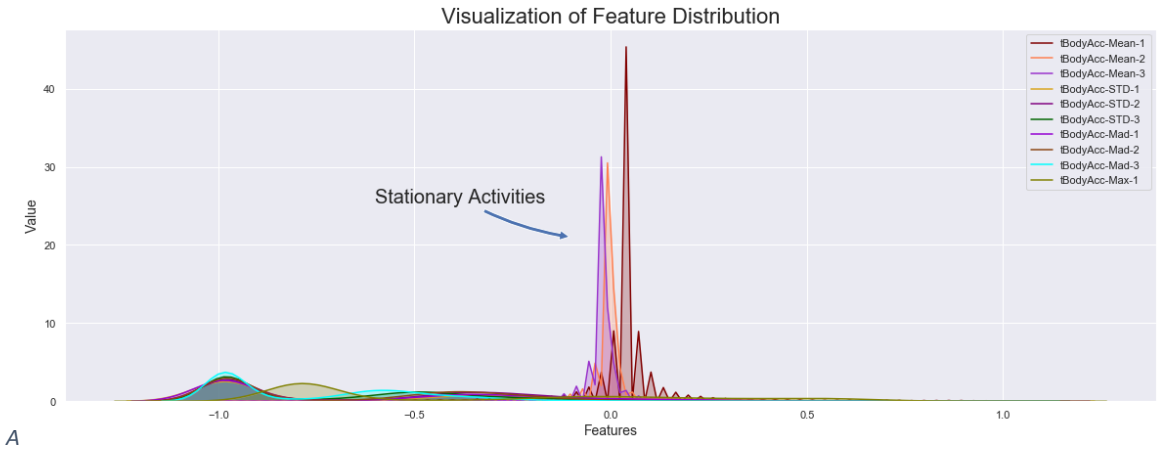


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Figure 9 Visualization of Feature Distribution plot 1

Figure 10 Visualization of Feature Distribution plot 2

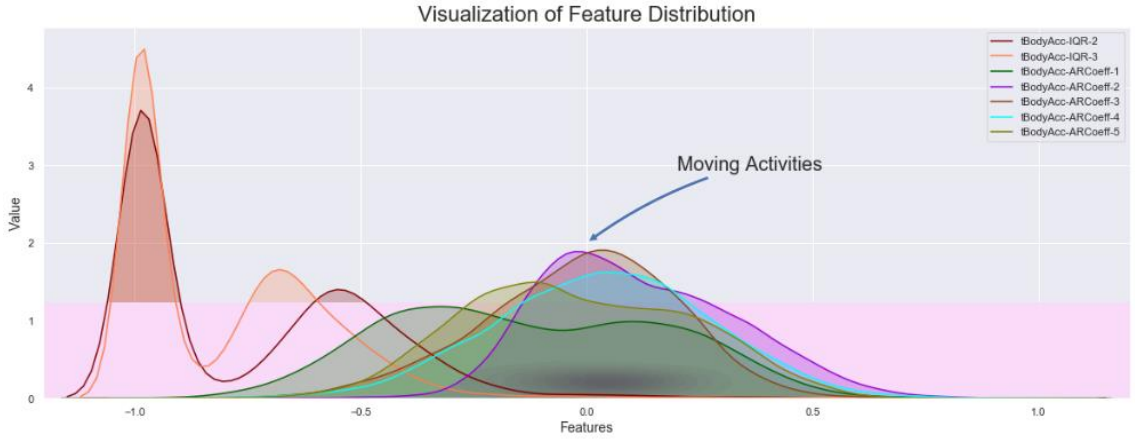

Figure 11 Visualization of Feature Distribution plot 3

2.2 Algorithms and Techniques

In this section, you will need to discuss the algorithms and techniques you intend to use for solving the problem. You should justify the use of each one based on the characteristics of the problem and the problem domain. Questions to ask yourself when writing this section:

- *Are the algorithms you will use, including any default variables/parameters in the project clearly defined?*
- *Are the techniques to be used thoroughly discussed and justified?*
- *Is it made clear how the input data or datasets will be handled by the algorithms and techniques chosen?*
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This stage of the activity recognition chain involves the training of a classification model that can discriminate the physical activity performed by a certain subject. Our objective is to eventually obtain a classifier that maximizes accuracy (i.e., the hit rate between the predicted and the actual class in a test set). The resulting classifier is intended to be used in a real-time cross-person prediction system that must be able to accurately predict the activity that a new user is performing.

This project addresses the HAR problem by applying different types of machine learning techniques: supervised learning using several classifiers (e.g. Logistic Regression, AdaboostClassifier, GradientBoostClassifier, K nearest Neighbors, Random Forest Classifier, Linear Support Vector Machines, and Stacking (a set of the classifiers). And finally, a basic Artificial Neural Network (ANN) is used to corroborate the results from the other classifiers. For each of the proposed algorithms, accuracy and a set of metrics are used as the common metrics to compare performances.

First, to prototype a fast evaluation system, Python's machine learning library, using "scikit-learn" a benchmark in performance was done using the robust method Logistic Regression.

The same data are input to different classifiers, and the results are stored for analysis. When selecting the classifiers, I used a wide set that includes classical and state-of-the-art techniques. I tested all the classifiers with various parameters, and the various parameters that were changed will be discussed in the sections below for each classifier's description. The classifiers with lower performances were discarded. The following classifiers were finally selected to be studied in more detail.

Table 2 Classifiers and Models Used

Classifier	
LogisticRegression	
AdaboostClassifier	
GradientBoostClassifier	
kn-Neighbors	
RandomForestClassifier	
LinearSVC	
Linear GridSearchSVC	
Stacking MetaClassifier	
ANN Neural Network Model	

2.2.1 Logistic Regression Methods

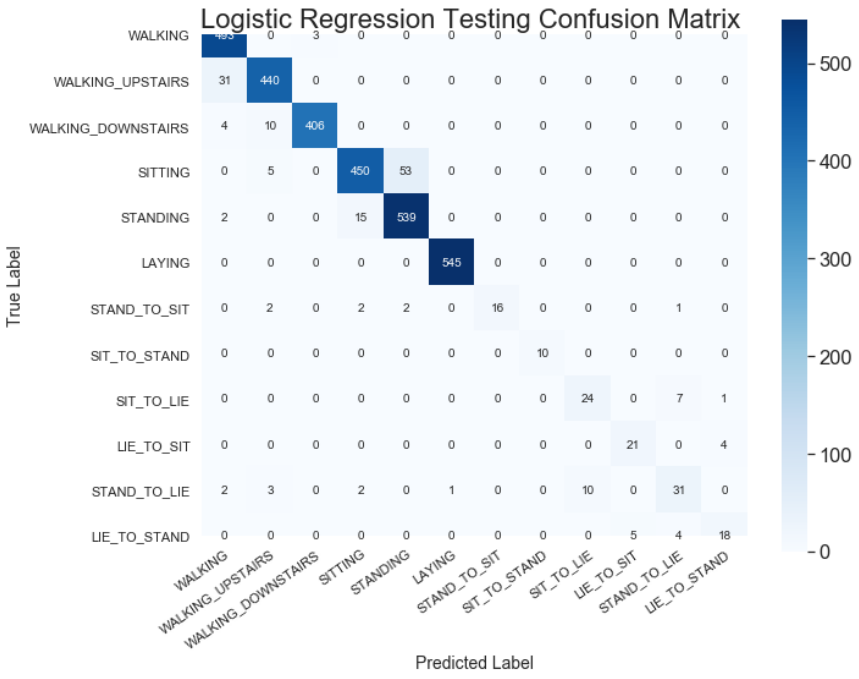
While Linear Regression is suited for estimating continuous values (e.g. estimating house price), it is not the best tool for predicting the class of an observed data point. In order to estimate the class of a data point, we need some sort of guidance on what would be the **most probable class** for that data point. For this, we use **Logistic Regression.**

Logistic Regression is a variation of Linear Regression, useful when the observed dependent variable, *y*, is categorical. It produces a formula that predicts the probability of the class label as a function of the independent variables.

Logistic regression fits a special *s*-shaped curve by taking the linear regression and transforming the numeric estimate into a probability with the following function, which is called sigmoid function.

The version of Logistic Regression in Scikit-learn, support regularization. Regularization is a technique used to solve the overfitting problem in machine learning models. **C** parameter indicates **inverse of regularization strength** which must be a positive float. Smaller values specify stronger regularization. Now lets fit our model with train set:

These techniques assume that data follow a probabilistic function that needs to be inferred. [1]

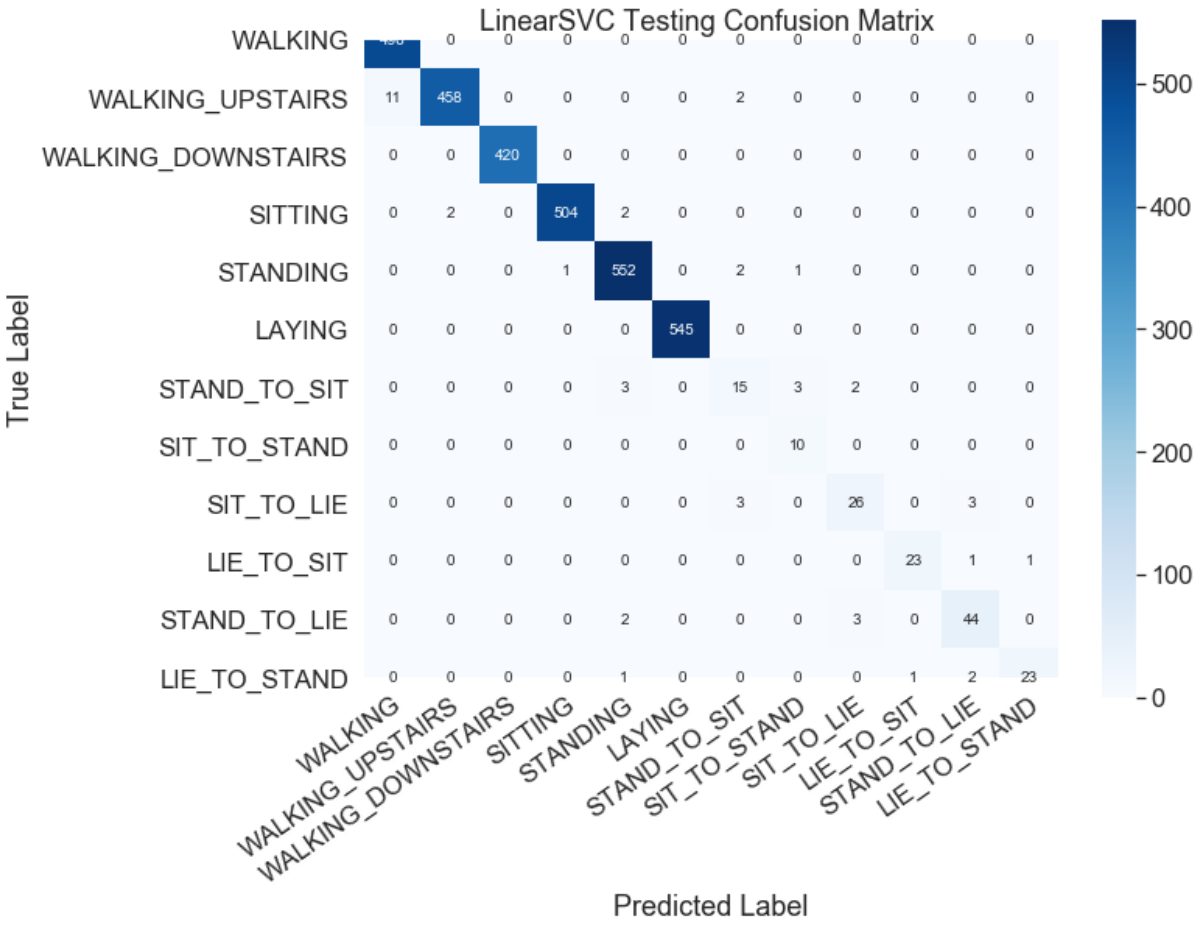


2.2.2 Support Vector Machines (SVM) Methods

These techniques build a model that predicts a target variable by learning interpretable decision rules inferred from the training data [61]. Using a decision tree as a predictive model is widely used as a decision support tool because they are easily interpreted (i.e., they provide a sequence of decisions to obtain the final classification result).

LinearSVC - As indicated by PCA there are 3 different sets activities are similar to each other and could be grouped together. Maximizing margins and separating the different activities may lead to a stronger performance. SVM Linear could be a good model to implement. Though it struggles to classify sitting/standing in some cases, they are both "static" type activities and in the context of activity or exercise tracking, could reasonably have lesser significance than the walking activities.

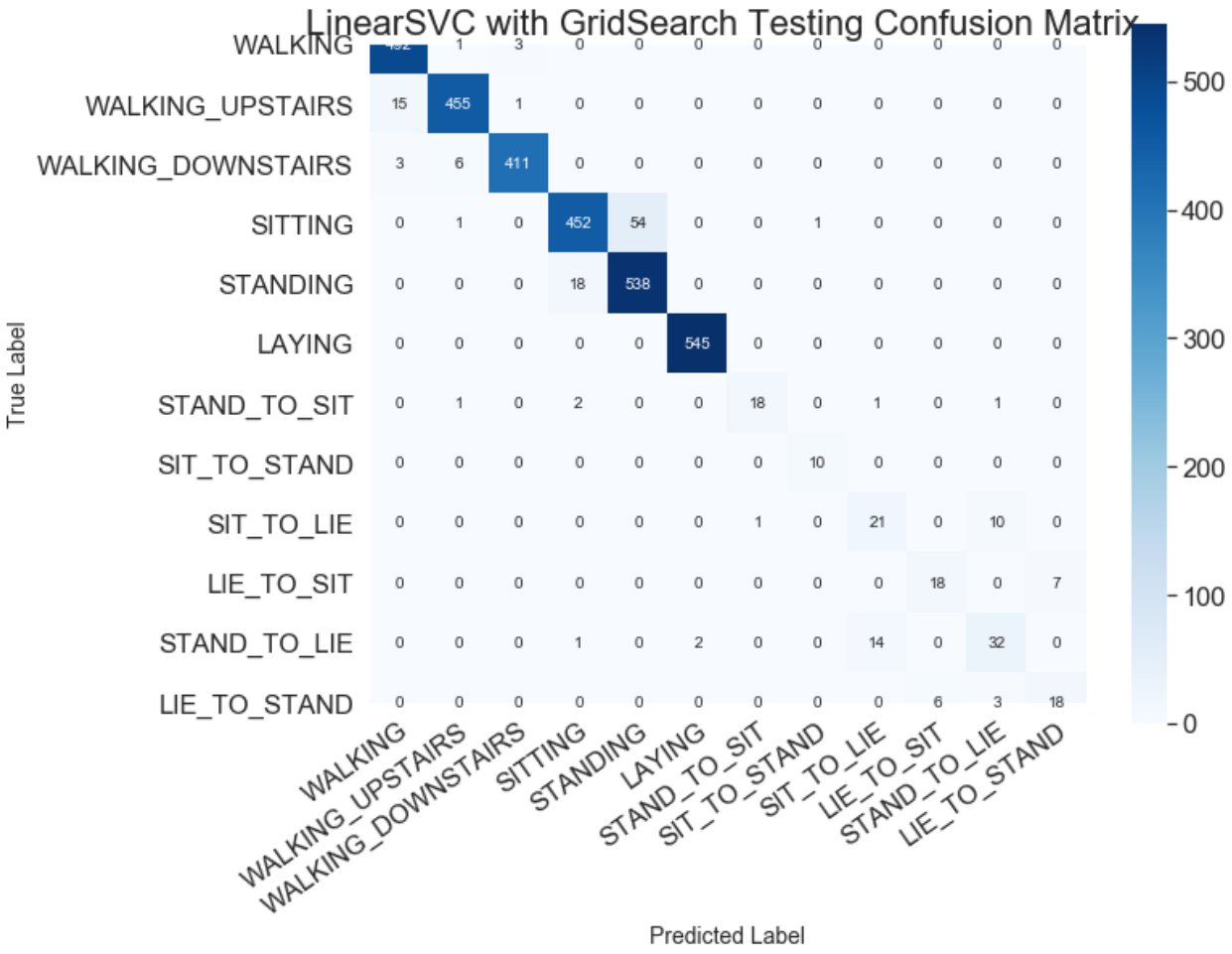
LinearSVC Classifier	n_estimators – ranged in a loop from 15 to 500
	max_features=5
	learning_rate=0.1 (performed runs with values of .01, .2 and accuracy went down from 93.2% to 91.1%, and 92.6%
	max_depth=3 (default)
	max_leaf_nodes=None,



LinearSVC with GridSearch

LinearSVC with GridSearch	n_estimators – ranged in a loop from 15 to 500
	max_features=5

Classifier	learning_rate=0.1 (performed runs with values of .01, .2 and accuracy went down from 93.2% to 91.1%, and 92.6%
	max_depth=3 (default)
	max_leaf_nodes=None,



SVM with linear kernel gives 96.7% accuracy on the test data - quite a strong performance.

Confusion matrix indicates there is still a bit of a struggle in classifying some sitting and standing activities. Reasonable for this to occur and natural variation between how people perform activities could plausibly explain the difference between train and test accuracy. Result may be hard to beat.

An Increase to accuracy score on second try by replacing the 'poly' kernel with linear' (95.19%)

The R2 score shows the highest so far of 0.9709256

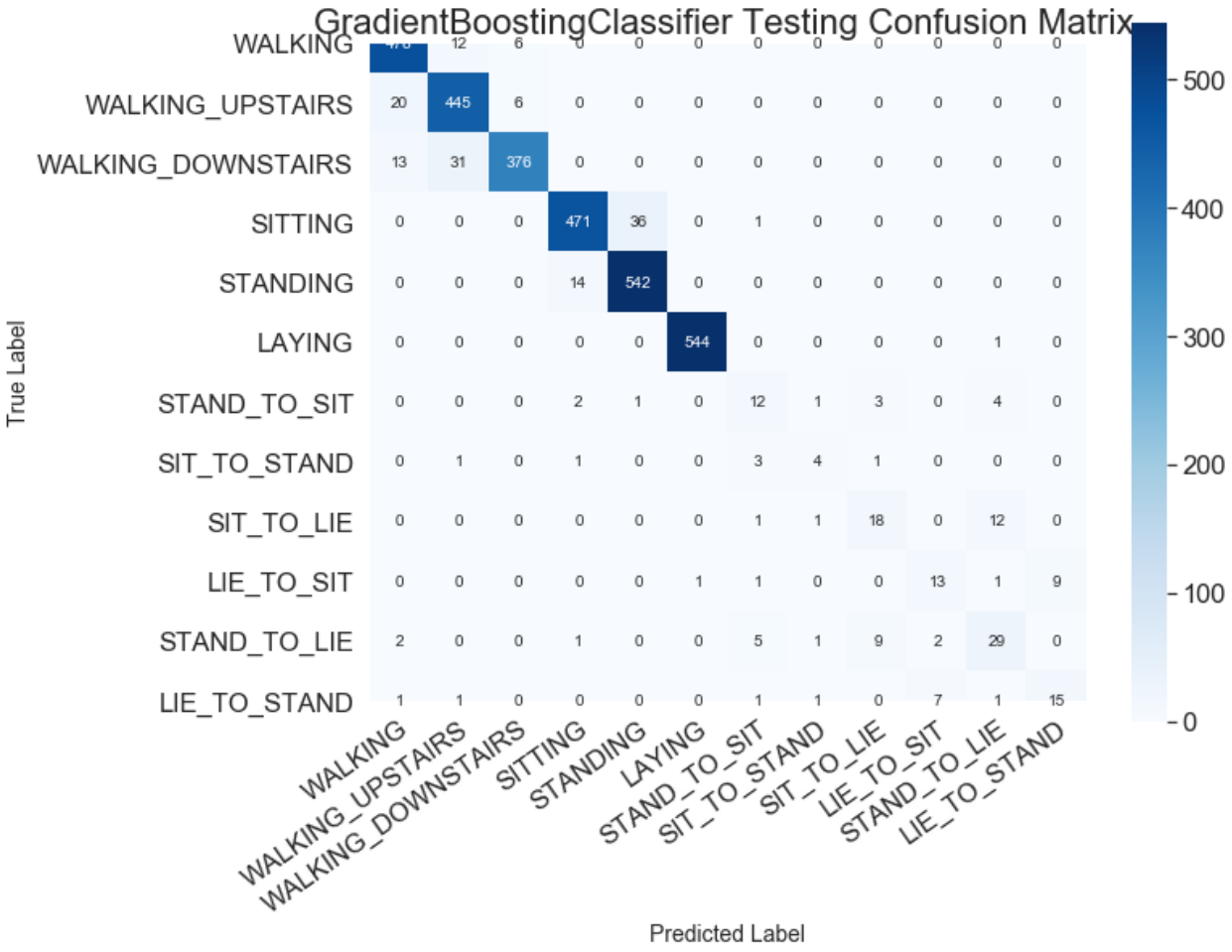
Our Support Vector Machine with Grid search with a linear kernel performed the best with 96-97% accuracy. A gridsearch did lead to a significant improvement to the model.

2.2.3 Decision Tree-Based Methods

These techniques build a model that predicts a target variable by learning interpretable decision rules inferred from the training data. Using a decision tree as a predictive model is widely used as a decision support tool because they are easily interpreted (i.e., they provide a sequence of decisions to obtain the final classification result).

Rf

GradientBoosting Classifier	n_estimators – ranged in a loop from 15 to 500
	max_features=5
	learning_rate=0.1 (performed runs with values of .01, .2 and accuracy went down from 93.2% to 91.1%, and 92.6%
	max_depth=3 (default)
	max_leaf_nodes=None,

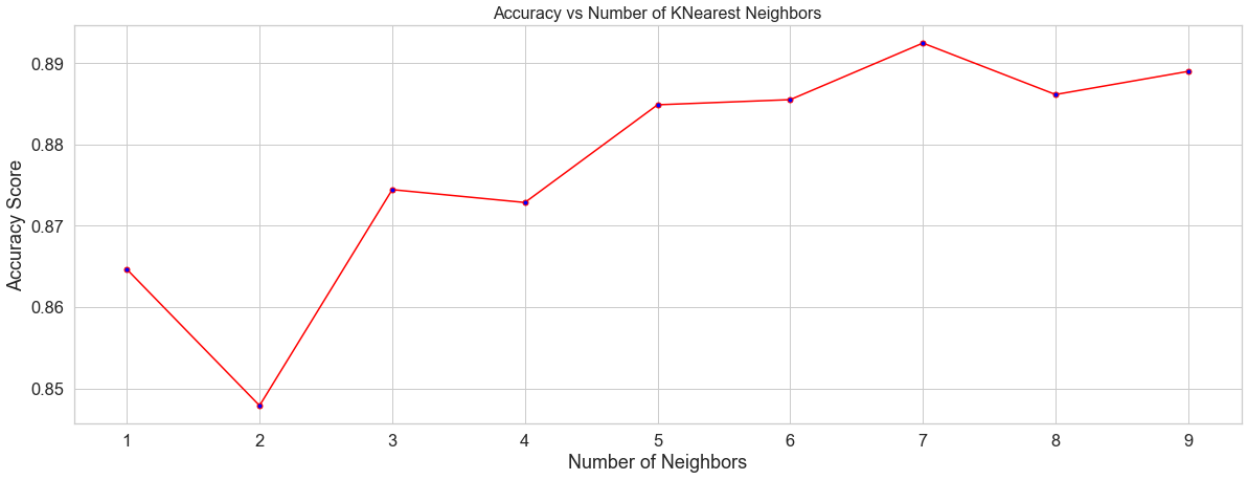


2.2.4 Distance-Based Methods

These algorithms assume that the data have some type of similarity and relations based on geometric properties and can be grouped according to these patterns. The k-nearest neighbors' algorithm (k-NN) is one of the simplest and most effective nonparametric machine learning algorithms for classification and regression. The K-nearest neighbors' method is a simple model, but requires that the same activity types mostly generate similar signal data. In our tests, the k-NN classifier obtained better results for online recognition when compared to a decision tree but was the worst overall performer of the classifiers that were used in this project. After testing several parameters, we eventually used the k-NN algorithm with the following scikit-learn parameters.

The K-nearest neighbors (Knn)

k-nearest neighbors' Classifier	n_estimators – ranged in a loop from 15 to 500
	max_features=5
	learning_rate=0.1 (performed runs with values of .01, .2 and accuracy went down from 93.2% to 91.1%, and 92.6%
	max_depth=3 (default)
	max_leaf_nodes=None,



2.2.5 Kernel Methods

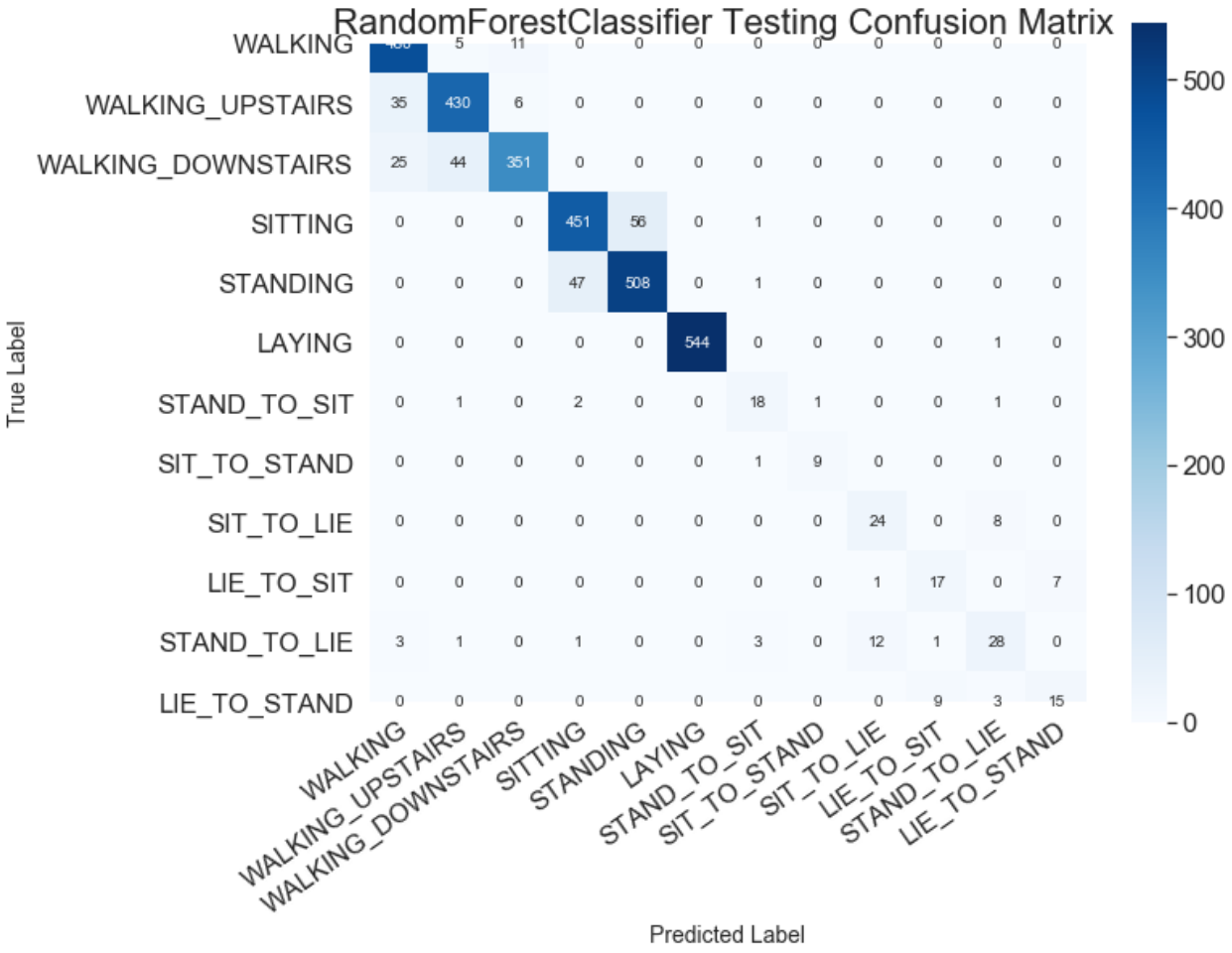
These models perform pattern analysis based on a kernel function, which is a similarity function over pairs of data points.

2.2.6 Ensemble Learners

These models combine the predictions of several base estimators built with a given learning algorithm to improve the results and robustness over a single estimator. Instead of picking just one of the machine learning solutions we have developed, we evaluate whether an ensemble of the models leans to an improved classification rate. This is because each of the standalone solutions have different strengths and weaknesses, and the compensation for the strengths and weaknesses between the models will generally lead to a better result of them all together in an ensemble.

Random Forest Classifier: The random forest did not perform as well most of the other classifiers that we tried, as our data is highly dimensional, and the randomness from bootstrap sampling so this classifier works better on data that is structured closer in types, such as just the six normal activities. Using just a subset of features may help correctly classify more activities.

Random Forest Classifier	n_estimators – ranged in a loop from 15 to 500
	max_features=5
	learning_rate=0.1 (performed runs with values of .01, .2 and accuracy went down from 93.2% to 91.1%, and 92.6%
	max_depth=3 (default)
	max_leaf_nodes=None,



GradientBoost classifier

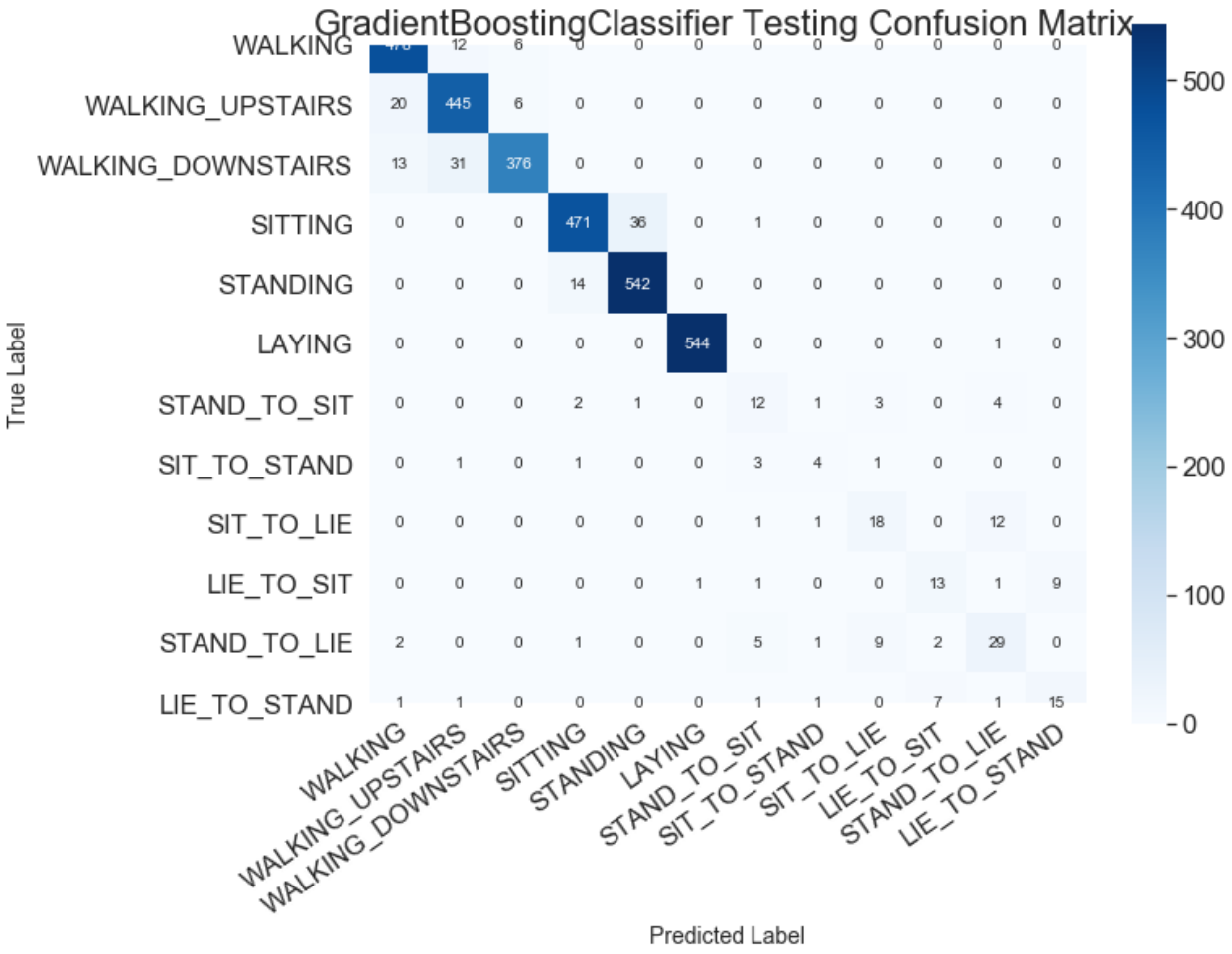
What is GB?

Good real-world applications of GB is anomaly detection in supervised learning settings where data is often highly unbalanced, in which our activities are different with static and moving classes. The strengths of the GradientBoosting model is that it performs very good for large datasets, reduces bias and variance, combines multiple weak predictors to a build strong predictor. **Weaknesses:** Some of the weaknesses of the GradientBoosting model is that it typically requires a relatively high training time, relative to Logistic Regression , and some over-fitting if the data sample is too small or if the data is noisy. Training generally takes longer because trees are built sequentially. Finally, the GB model does require complex tuning. There are typically three parameters: number of trees, depth of trees and learning rate, and each tree built is generally shallow.

The parameters that we used that were the final parameters use were

GradientBoosting Classifier	n_estimators – ranged in a loop from 15 to 500
	max_features=5

	learning_rate=0.1 (performed runs with values of .01, .2 and accuracy went down from 93.2% to 91.1%, and 92.6%
	max_depth=3 (default)
	max_leaf_nodes=None,



AdaBoost classifier is a meta-estimator that begins by fitting a classifier on the original dataset and then fits additional copies of the classifier on the same dataset but where the weights of incorrectly classified instances are adjusted such that subsequent classifiers focus more on difficult cases. The default base-estimator used was Decision Tree. The core principle of AdaBoost is to fit a sequence of weak learners (i.e., models that are only slightly better than random guessing, such as small decision trees) on repeatedly modified versions of the data. The predictions from all of them are then combined through a weighted majority vote (or sum) to produce the final prediction. [9]

AdaBoost Classifier	n_estimators – ranged in a loop from 15 to 500
	max_features=5

	learning_rate=0.1 (performed runs with values of .01, .2 and accuracy went down from 93.2% to 91.1%, and 92.6%
	max_depth=3 (default)
	max_leaf_nodes=None,

Stacking

We use stacking to determine whether we can get an improvement in performance compared to the standalone models. In stacking, we first input the training data into several classifiers, i.e. C1, C2, C3, etc,, next we perform Level one predictions, i.e P1, P2, P3), then we could extend to a Level 2 prediction, by taking the Level 1 predictions from the k-fold cross-validation from each of the standalone models (level one predictions, i.e P1, P2, P3) and append them to the original training dataset. We then train on this original feature plus layer one predictions dataset using k-fold cross-validation, resulting in layer two (Level 1 and Level 2) predictions in this "Meta-Classifier". And from this it will be evaluated to see if we have an improvement over any of the standalone models. This is a graphical depiction of the simple model of stacking using only a Level 1 prediction. In this project, we will use this simple version of the stacking model

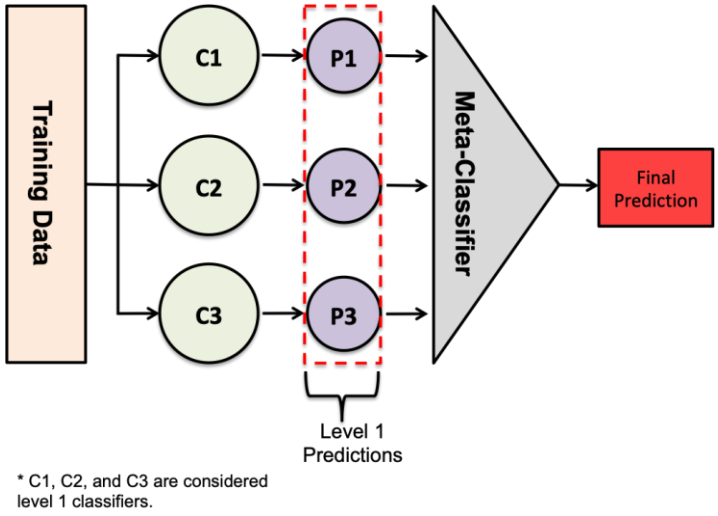
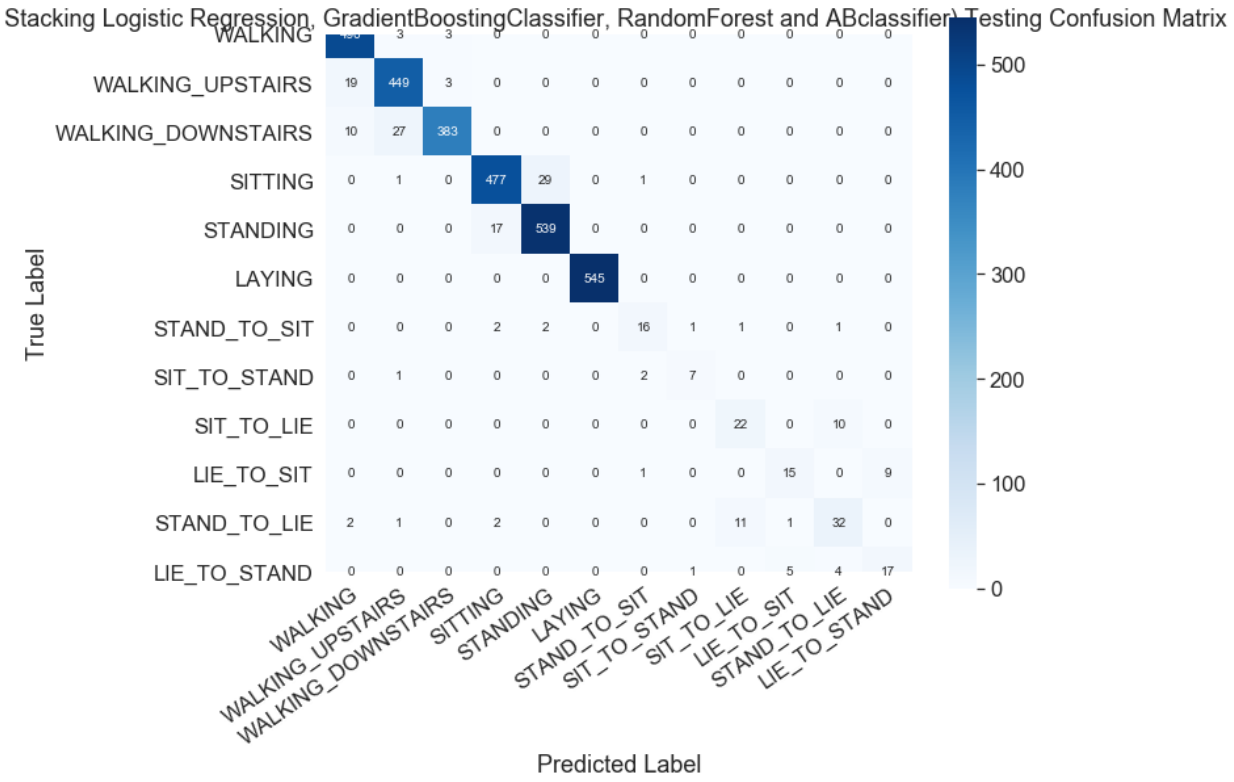


Figure 12 Stacking Model Overview

Stacking model Meta-Classifier	n_estimators – ranged in a loop from 15 to 500
	max_features=5
	learning_rate=0.1 (performed runs with values of .01, .2 and accuracy went down from 93.2% to 91.1%, and 92.6%
	max_depth=3 (default)

	max_leaf_nodes=None,



2.2.7 Neural Networks

Finally a basic artificial neural network (ANN) approach specifically adjusted for the best performance for this classification problem was approached.

Artificial neural networks are based on the idea of modeling problems with high-level abstractions in data by using multiple processing layers that basically perform multiple non-linear transformations. [13]

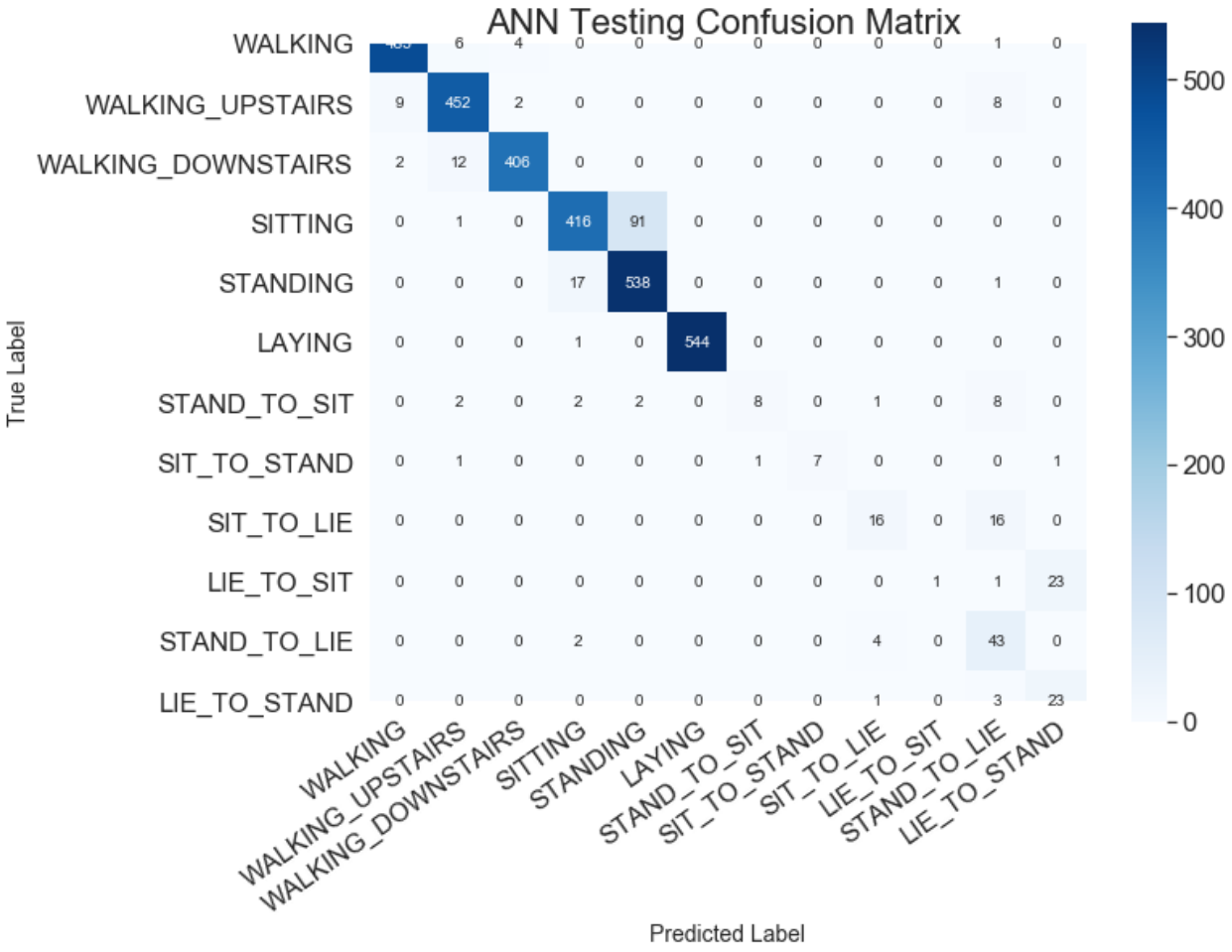
Given the accuracy on testing data is much lower than that on the training data, the algorithms appeared to suffer from overfitting. Applying deep neural network could also help reduce overfitting. Alternatively, some form of regularization, we use a layer called DENSE with "relu" activation, to penalize overfitting which may be helpful to alleviate overfitting.

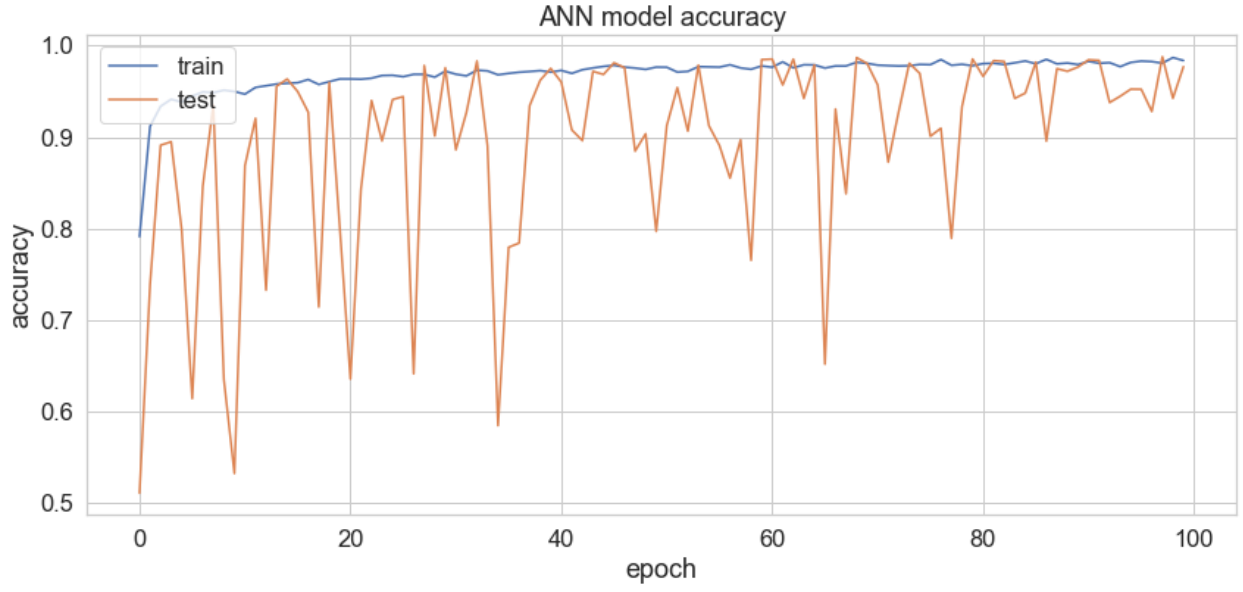
Table 3 Final ANN Model Summary (Sequential Layers)

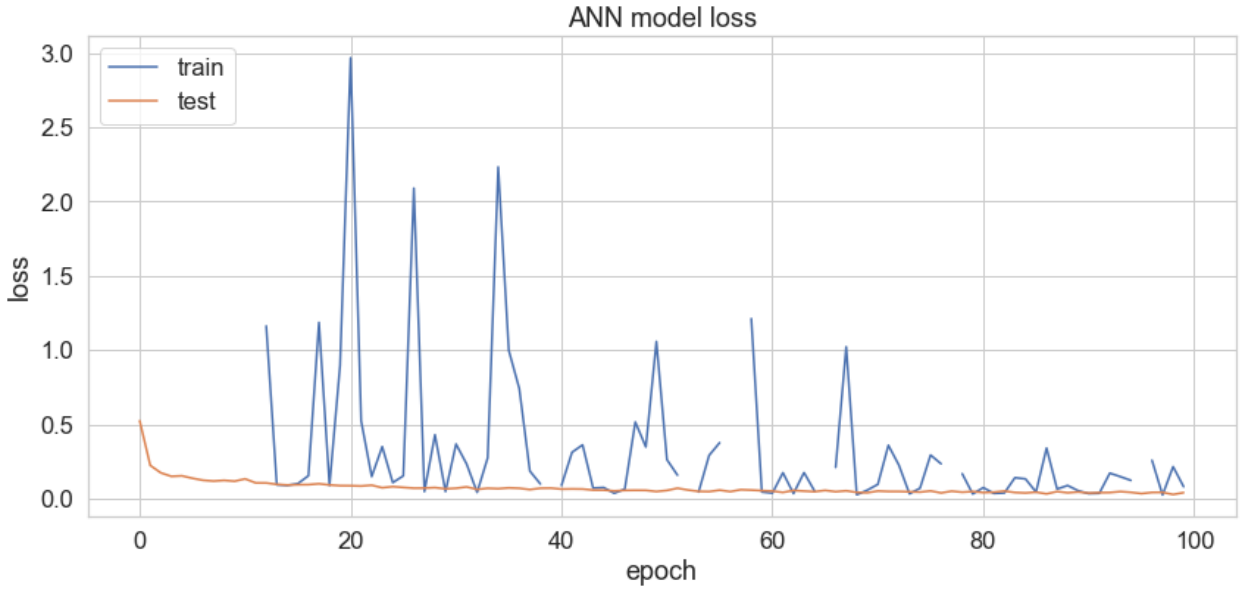
```
model.summary()

Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_6 (Dense)              (None, 768)               431616
_________________________________________________________________
dense_7 (Dense)              (None, 128)               98432
_________________________________________________________________
batch_normalization_1 (Batch (None, 128)               512
_________________________________________________________________
dense_8 (Dense)              (None, 128)               16512
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_9 (Dense)              (None, 196)               25284
_________________________________________________________________
dropout_3 (Dropout)          (None, 196)               0
_________________________________________________________________
dense_10 (Dense)             (None, 32)                6304
_________________________________________________________________
dense_11 (Dense)             (None, 12)                396
=================================================================
Total params: 579,056
Trainable params: 578,800
Non-trainable params: 256
```

ANN Model 1	n_estimators – ranged in a loop from 15 to 500
	max_features=5
	learning_rate=0.1 (performed runs with values of .01, .2 and accuracy went down from 93.2% to 91.1%, and 92.6%
	max_depth=3 (default)
	max_leaf_nodes=None,


ANN Testing Confusion Matrix
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
SITTING
STANDING
LAYING
STAND_TO_SIT
SIT_TO_STAND
SIT_TO_LIE
LIE_TO_SIT
STAND_TO_LIE
LIE_TO_STAND
True Label
Predicted Label
500
400
300
200
100
0


ANN model accuracy
train
test
accuracy
epoch
1.0
0.9
0.8
0.7
0.6
0.5
0
20
40
60
80
100



2.3 Benchmark

In this section, you will need to provide a clearly defined benchmark result or threshold for comparing across performances obtained by your solution. The reasoning behind the benchmark (in the case where it is not an established result) should be discussed. Questions to ask yourself when writing this section:

- *Has some result or value been provided that acts as a benchmark for measuring performance?*
- *Is it clear how this result or value was obtained (whether by data or by hypothesis)?*

The benchmark model that will be used for measuring performance will be a logistic regression model for a classification to develop a baseline activity recognition model. The reasoning behind using this benchmark because LR is a good candidate because our problem consists of doing binary classification with clean data, which makes for good conditions for the logistic regression model. It's fast, so we can evaluate the best options, i.e changes to features, or thresholds quickly. Logistic regression would provide great flexibility should we get additional data or decide to experiment with different thresholds, i.e, different type of sensors providing.

The benchmark model will then be compared to the different standalone models, and then to the ensemble, then the stacking, and then the ANN models predictions.

Logistic Regression is a statistical method for predicting binary classes. The outcome or target variable is binary in nature. It computes the probability of an event occurrence. Logistic Regression is very widely used on Financial forecasting, crime data mining, and binary classification problems,

We will build our benchmark model using LogisticRegression from Scikit-learn package. This function implements logistic regression and can use different numerical optimizers to find parameters, including ‘newton-cg’, ‘lbfgs’, ‘liblinear’, ‘sag’, ‘saga’ solvers. The version of Logistic Regression in Scikit-learn, supports regularization. Regularization is a technique used to solve the overfitting problem in machine learning models.

3 Methodology

3.1 Data Preprocessing

Before data can be used as input for machine learning algorithms, it often must be cleaned, formatted, and restructured — this is typically known as preprocessing. Fortunately, for this dataset, there are no invalid or missing entries we must deal with, however, this is some formatting of the dataset required for some of the models and there are some qualities about certain features that must be adjusted. Reformatting that data based on refinement optional ideas presented for future work would help tremendously with the outcome and predictive power of nearly all learning algorithms. The preprocessing steps were as follows:

Data Preparation and Exploration

Explored and established a basic understanding of the dataset, performed basic cleaning and processing, transform the data into examples and explore the data to show the distribution information of the dataset.

a) Loading the data, transformations of the data, data exploration and data reformatting.
b) Perform Data Cleaning.
c) Split the dataset into a Training and Testing set.
d) Collect Statistics about the dataset.
e) Display the dataset to view for correctness and format.

Visualization of Feature Distribution

Sets of plots were created to examine the data

f) Plot Number of Samples per Activity
g) Plot Samples of Activities provided by each Test Subject
h) Plot of 3 Axis Body Acceleration Mean Values with Respect to Frequency vs the Activity Type
i) Plot Visual exploration of the data in 3 dimensions with principal component analysis
j) Plot Explained Variance by No. of Principal Components.

Features Engineering

k) Develop concepts about new features could be developed based on the given features.
l) Determine Approaches to Modeling the Problem

ANN Model Preprocessing Steps Required:

m) Removed Subject and Activities column from the dataset, subject info not needed for basic ANN training, and Activities get converted to one-hot encoded.
n) Categorical labels encoded using by using a technique called One-hot Encoding
o) Convert the Training and Test set data to NumPy arrays.
p) Set the set the input shape to a one-dimensional array.

3.2 Implementation

In this section, the process for which metrics, algorithms, and techniques that you implemented for the given data will need to be clearly documented. It should be abundantly clear how the implementation was carried out, and discussion should be made regarding any complications that occurred during this process. Questions to ask yourself when writing this section:

- *Is it made clear how the algorithms and techniques were implemented with the given datasets or input data?*
- *Were there any complications with the original metrics or techniques that required changing prior to acquiring a solution?*
- *Was there any part of the coding process (e.g., writing complicated functions) that should be documented?*
    - ---

The goal is to implement models that demonstrate a comparison between the traditional classification models to a basic ANN, and understanding any improvements in terms of computational costs while maintaining similar accuracy. We implement these models using primary using the following commonly available libraries that we import and include numpy's, pandas, mathplotlib, and sklean.

3.2.1 We use the following libraries and examples to implement the data manipulation, plotting, the model fitting and training, and evaluation.
numpy and pandas: NumPy enables us to work with arrays with great efficiency. Pandas is used to read the dataset file and import it as a dataframe, which is like a table with rows and columns.

```
# Panda csv function to import The Training dataset

X_train = pd.read_csv('./data/HAPT Data Set/Train/X_train.txt', sep='\s+', header=None)
```

```
#converting training data into numpy array

from numpy import array

  aX_train=X_train.values
```

matplotlib: matplotlib is a highly customizable package which has the sub package pyplot that enables us to draw plots, bar charts, pie charts and more. We get options to add legends, axis titles, change thickness of lines etc. The cm package (colormap) allows us to get colors for our charts.

sklearn: This machine learning library includes numerous machine learning algorithms already built-in with certain parameters set as default parameters, so they work right out of the box.

For example:

```
# Fitting Logistic Regression to the Training set

 from sklearn.linear_model import LogisticRegression

# print classification report of Precision-Recall, f1-score accuracy scores

from sklearn.metrics import confusion_matrix, classification_report

from sklearn.metrics import classification_report, accuracy_score
```

3.2.2 Creating a Training and Predicting Pipeline for the learning algorithms

To properly evaluate the performance each model chosen, we created a training and predicting pipeline that allows to quick and effective training models using various sizes of training data and perform predictions on the testing data. The basics steps to implement the learning classifiers are as follows:

a. **INPUT Data for Training:** The input data for all sci-learn learning algorithms except for the ANN Neural Network is the **X_train** data as shown in the example in figure 2. Which is the csv panda import of the data from the HAR dataset. No manipulations were done on the final training runs. Scaling was not used, it is left in the jypter notebook and used for earlier trial runs, but not used in the final.

b. **INPUT Data for Testing Predictions**: Likewise to the training data, The input data for all sci-learn learning algorithms except for the ANN Neural Network is the **X_test** data as shown in the example in figure 2.

c. Import the libraries like this

```
from sklearn.linear_model import LogisticRegression
```

d. configure the algorithm for the learning classifier

```
LogisticRegression(random_state = 0, solver= 'lbfgs')
```

e. Fit the learner to the sampled training data and record the training time.

```
LRresults = LRclassifier.fit(X_train, y_train)
```

f. Perform predictions on the test data X_test, and also on the training points X_train.

```
# Predicting the Training set results

LR_pred_train = LRclassifier.predict(X_train)

# Predicting the Test set results

y_pred = LRclassifier.predict(X_test)
```

In this way we validate the training was performed adequately and is 100% or 99% on all except k-neighbors training.

g. Record the total prediction time.

h. Calculate the accuracy score for both the training subset and testing set.

i. **Calculating the Confusion Matrix, the classification** report was written as a function builds a text report showing the main classification metrics. # precision is the ability of the classifier not to label as positive a sample that is negative and recall is the ability of the classifier to find all the positive sample. Matplotlib and sns.heatmap is used to layout the confusion matrix.

A Normalization of the confusion matrix is also performed, like this:

```
normalized_confusion_matrix = np.array(cm, dtype=np.float32)/np.sum(cm)*100
```

Calculate the Precision, Recall, F1 score for the testing set. For each individual run of all the experiments conducted, accuracy, precision, recall and F1, R2 and MCC scores are collected. The accuracy metric is simply the percentage of correctly-classified instances. Although the dataset used for this work is not perfectly balanced, because we are working with twelve classes, we consider that average accuracy metric to be both a simple and appropriate metric for representing the classifiers' overall performances. For this reason, and to aid readability, we summarized only the accuracy metric plus variance for the preliminary evaluation. Of course, we also analyzed the confusion matrix, precision, recall, F1. Because this is a multiclass problem, these metrics are obtained by weighted averaging.

j. Calculate the R2 Score

```
# The r2_score function

from sklearn.metrics import r2_score LRr2 = r2_score(y_test, y_pred) print
("r2 score: %.4f" %(LRr2))
```

k. Calculate the Mathews correlation coefficient.

```
# "The Matthews correlation coefficient

from sklearn.metrics import matthews_corrcoef LR_mc = matthews_corrcoef(y_test,
y_pred) print('matthews_corrcoef: ', LR_mc) print ("matthews_corrcoef: %.4f"
%(LR_mc))
```

3.2.3 Creating a Training and Predicting Pipeline for the artificial neural network

For the ANN, the following differences was use to pre-process the input data, One-hot-encode, convert to Numpy arrays, and set one dimensional.

l. **ONE-HOT-ENCODE**: For the y_train and y_test labeling data. From the table in Exploring the Data for the activities, we can see there are several features for each record that are non-numeric. Typically, learning algorithms expect input to be numeric, which requires that non-numeric features (called categorical variables) be converted. One popular way to convert categorical variables is by using the one-hot encoding scheme. One-hot encoding creates a "dummy" variable for each possible category of each non-numeric feature. For example, assume someFeature has three possible entries: A, B, or C. We then encode this feature into someFeature_A, someFeature_B and someFeature_C.

| | someFeature | | someFeature_A | someFeature_B | someFeature_C | | :-: | :-: | | :-: | :-: | :-: | | 0 | B | | 0 | 1 | 0 | | 1 | C | ---> one-hot encode ----> | 0 | 0 | 1 | | 2 | A | | 1 | 0 | 0 |

```
# one hot encode implementation do for both Training and Testing label data
# reference: https://machinelearningmastery.com/how-to-one-hot-encode-sequence-data-in-python/
from sklearn.preprocessing import OneHotEncoder

onehotencoder = OneHotEncoder()

one_hot_enc_y_train = onehotencoder.fit_transform(y_train).toarray()

one_hot_enc_y_test = onehotencoder.fit_transform(y_test).toarray()
```

m. convert to Numpy arrays

```
from numpy import array

aX_test = X_test.values #converting test data into array
```

n. Set INPUT SHAPE to one dimensional.

```
# set the input shape

input_dim = 561,
```

3.3 Refinement

In this section, you will need to discuss the process of improvement you made upon the algorithms and techniques you used in your implementation. For example, adjusting parameters for certain models to acquire improved solutions would fall under the refinement category. Your initial and final solutions should be reported, as well as any significant intermediate results as necessary. Questions to ask yourself when writing this section:

- *Has an initial solution been found and clearly reported?*
- *Is the process of improvement clearly documented, such as what techniques were used?*
- *Are intermediate and final solutions clearly reported as the process is improved?*
    - ----------

The solution to our problem will be summarized in the results section, but here we discuss the process of improvements made upon the algorithms and techniques used in the implementation.

Scaling of the datasets was looked at earlier in the project in the LR benchmark algorithm, but not included in the final training results because a brief try of scaling in the benchmark did not improve the results. It can be recommended to implement scaling, now looking back on the visualization and analysis of the results, scaling implemented taking into some of the considerations noted in the data exploration and results section of this report.

Tweeked KN,

ANN refinement would be to better class balance the input data to the ANN.

Created tables of the before and after results for at least 3 of the classifiers.

Logistic Regression > solver= 'lbfgs') implements logistic regression and can use different numerical optimizers to find parameters, including ‘newton-cg’, ‘lbfgs’, ‘liblinear’, ‘sag’, ‘saga’ solvers.

n_estimators > from 15 to 500

The random forest did not perform as well most of the other classifiers that we tried, as our data is highly dimensional, and the randomness from bootstrap sampling so this classifier works better on data that is structured closer in types, such as just the six normal activities. Using just a subset of features may help correctly classify more activities.

LinearSVC - As indicated by PCA there are 3 different sets activities are quite similar to each other and could be grouped together. Maximizing margins and separating the different activities may lead to a stronger performance.

‘;

AdaBoost Classifier*, Using LR=0.01, and algorithm change from the default SAMME to SAMMR, with the base-estimator the DecisionTree Classifier*. The SAMME.R real boosting algorithm typically converges faster than SAMME, achieving a lower test error with fewer boosting iterations.

The base-estimator Classifiers

base = DecisionTreeClassifier(max_features=5, max_depth=6)

base = RandomForestClassifier(max_features=5, max_depth=6)

Two algorithms can be used here: SAMME and SAMME.R

ABclassifier = AdaBoostClassifier(base_estimator=base, n_estimators=n_trees,

learning_rate=0.01, random_state=42, algorithm="SAMME")

LinearSVC gridsearch

kN N adjustments

ANN improvements

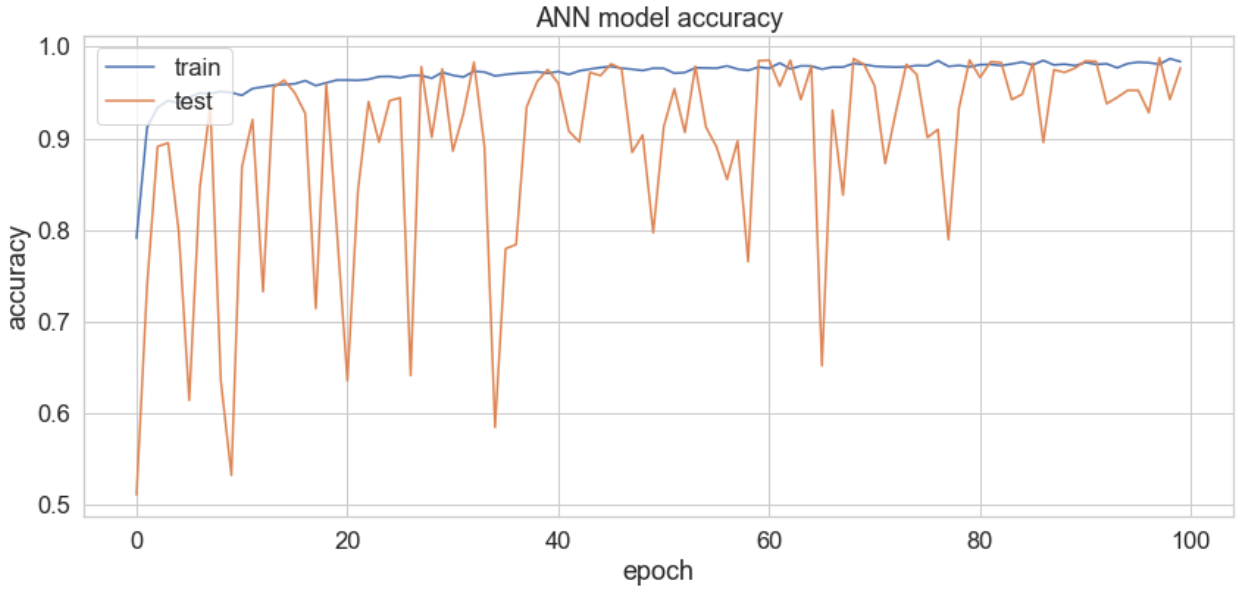


Figure 13 Artificial Neural Network Model Accuracy= vs. epoch results

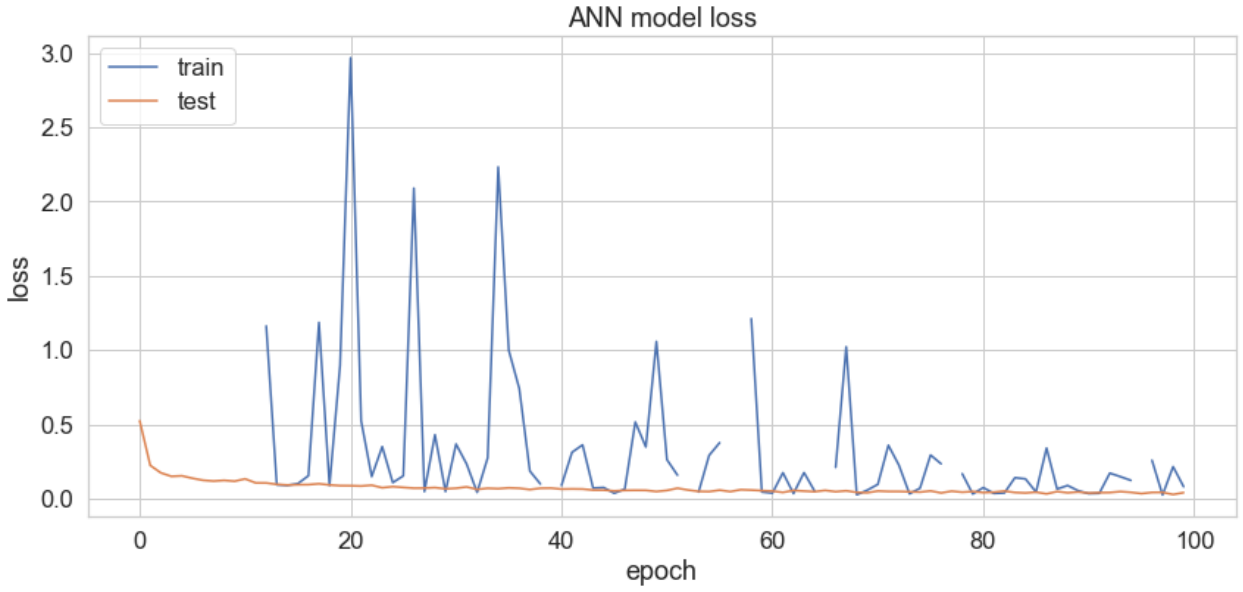


Figure 14 Artificial Neural Network Model Loss vs. epoch results

4 Results

(approx. 2-3 pages)

4.1 Model Evaluation and Validation

In this section, the final model and any supporting qualities should be evaluated in detail. It should be clear how the final model was derived and why this model was chosen. In addition, some type of analysis should be used to validate the robustness of this model and its solution, such as manipulating the input data or environment to see how the model's solution is affected (this is called sensitivity analysis). Questions to ask yourself when writing this section:

- *Is the final model reasonable and aligning with solution expectations? Are the final parameters of the model appropriate?*
- *Has the final model been tested with various inputs to evaluate whether the model generalizes well to unseen data?*
- *Is the model robust enough for the problem? Do small perturbations (changes) in training data or the input space greatly affect the results?*
- *Can results found from the model be trusted?*
    - ----------

Our Support Vector Machine with a linear kernel performed the best with 96-97% accuracy. A gridsearch did lead to a significant improvement to the model.

The final model was derived…. And the model was chosen because…..

The analysis xxxx. Was used to validate the robustness of the model……

Changes made to the LR, SVM, and ensemble learner classifiers typically only made small % changes to the accuracy results, such as a difference between 94% to 93%, or 90%. For adjustment tests on the distance learning classifiers, results above the 89% were not obtainable. For Stacking, the trys of the different models varied down to worst case in the 85%. For the basic ANN, improperly set with hyperparameters lead to very wild swings of the results, such as when you run the training under 60 epochs, or when the weights get randomly set wrong, you will occasionally get unpredictable results came out below 80% as can seen in the "Artificial Neural Network Model Accuracy= vs. epoch results" chart. For the data method i. e. class imbalance used on the input to this basic ANN model, you need to use at least 90 epochs, however, I did get unpredictable results at 120 and over epochs.

Table 4 Results of the Classifiers/Models by Training, Accuracy, R2, MCC

Classifier	Training Time (Sec)	Accuracy	R2 Score	MCC score
LogisticRegression	10.84	0.94655	0.939	0.937
AdaboostClassifier	137.88	0.93707	0.94	0.926
GradientBoostClassifier	78.82	0.93201	0.926	0.92
kn-Neighbors	229.98	0.88899	0.895	0.87
RandomForestClassifier	101.75	0.90923	0.932	0.893
LinearSVC	7.41	0.94624	0.931	0.937
Linear GridSearchSVC	110.64	0.95193	0.971	0.943
Stacking	206.11	0.94782	0.95	0.939
ANN Neural Network Model	656.05	0.92948	0.905	0.918

Due to class imbalance presented in the data, a robust methodology is required to examine accuracy together with a confusion matrix to understand where the errors were coming from.

Both the fine-tuned XXx, XXX, XXX, models and the ANN applied over the entire dataset outperformed the benchmarking model. There is little surprise given the models were performed over larger datasets with fine-tuned hyper parameters to optimize accuracy scores. In addition, since the XXX, XXX, XXx and ANN models achieved over 9x% accuracy on the testing datasets, it is considered as appropriate solution to address the HAR problem adequately.

We have success in finding optimizing a model in which is higher than our benchmark with, the final highest accuracy is of 95% using the Linear SVC with grid search, and with an average training time of all the 8 models. We can see that the ANN can peak to values above the training average at some moments during the training, depending on how the neural network's weights got initialized at the start of the training epoch, randomly.

This means that the neural networks is almost always able to correctly identify the movement type!

4.2 Justification

In this section, your model's final solution and its results should be compared to the benchmark you established earlier in the project using some type of statistical analysis. You should also justify whether these results and the solution are significant enough to have solved the problem posed in the project. Questions to ask yourself when writing this section:

- *Are the final results found stronger than the benchmark result reported earlier?*
- *Have you thoroughly analyzed and discussed the final solution?*
- *Is the final solution significant enough to have solved the problem?*
    - ---

5 Conclusion

5.1 Free-Form Visualization

In this section, you will need to provide some form of visualization that emphasizes an important quality about the project. It is much more free-form but should reasonably support a significant result or characteristic about the problem that you want to discuss. Questions to ask yourself when writing this section:

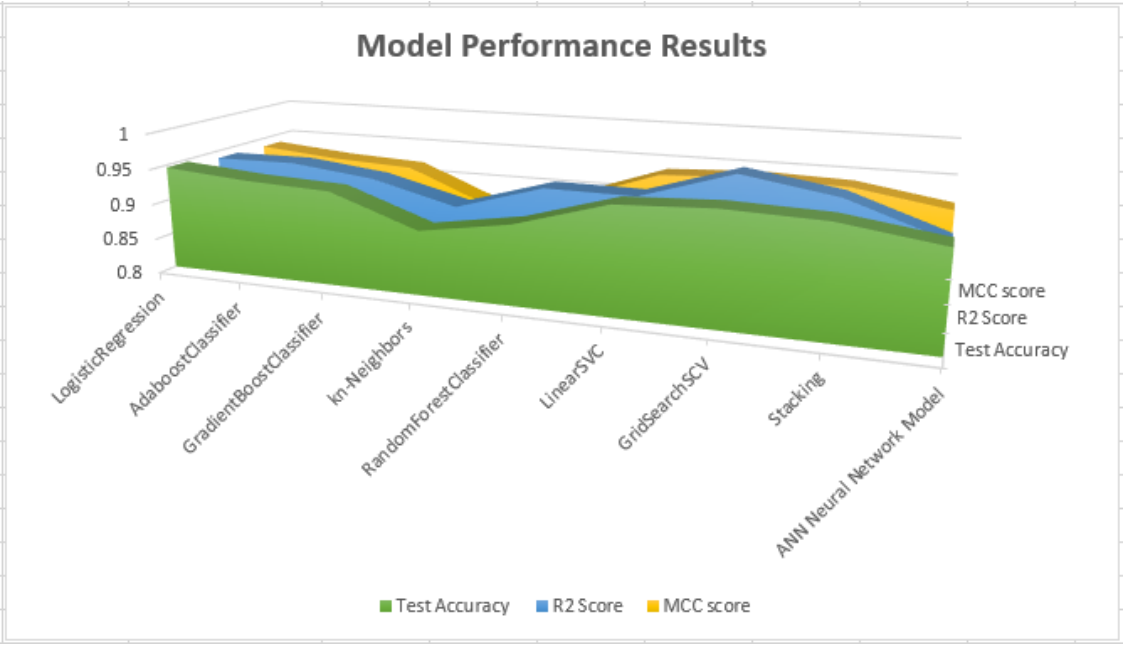


Figure 15 Classifier Performance Visualization

Figure 16 Classifier Training Time (Seconds) `

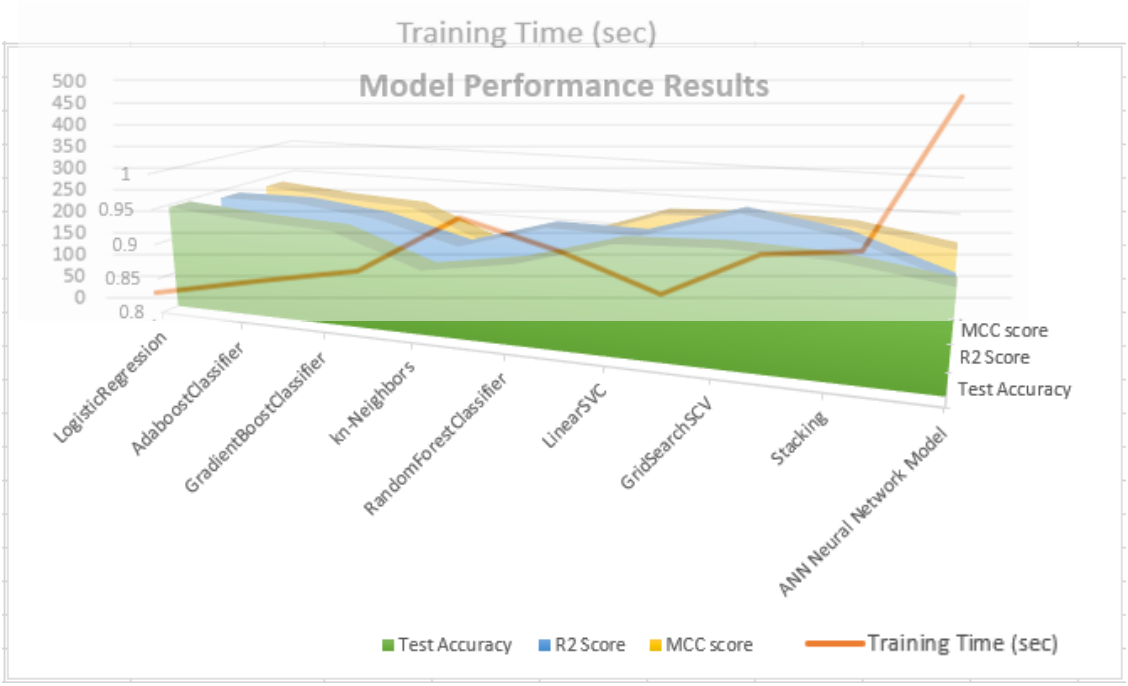


Table 5 A Visual Overlay of Performance vs. Training Time Results of the Final models

5.2 Reflection

This project helped give me a great understanding of the learning algorithms and the basic artificial neural network, and the coding required for it. There is quite a bit of further coding optimization that can be done to optimize the pipeline to get the models displaying information that provides guidance on ways to tune for better performance.

The most difficult aspect of the project was the determination and implementation of the preprocessing steps required for the Neural Network. But with much research and experimentation, a solution was found for the basic implementation. I found that Quora, StackOverflow, and other StackExchange sites, and of course the Udacity Mentor are good places for asking questions and finding answers.

Much work was put in by the researchers to preprocess the dataset and by providing labeled data, enabling the work for the study for this project to focus purely on applying machine learning techniques and focusing on improving the model performance. However, such well treated dataset is rare in practice. I

In designing a suitable neural network structure, there are multiple combinations of hyperparameters, and different types of neural networks layers can be further applied for evaluation. But for this project, several different types of neural networks can be developed to make much better models to handle this type of data to reach toward the goal of being able to recognize a wide variety of human activities. This include Convolutional Neural Networks (CNN's), and Long Term Short Term Memory (LSTM) which are Recurrent Neural Networks. See [14] for example.

5.3 Improvement

Since Linear GridsearchSVC performed overall the best in this project, I would recommend starting further work with this model and further fine-tune the grid search function to further improve the model performance. Suggest breaking the input dataset according to methods in the data exploration process determined could provide for more balance among input groups. Can it be optimized to run faster, but with the same results? Scaling was not used in these final results, but evaluation of the best way to do scaling of the data should be done next. Use of the raw dataset which can be found at [1] could also be explored to see whether the preprocessing procedures have significant impact on model performance.

In addition, given the errors were predominantly present in transitioning activities, partitioning out the static and non-static (postural transitions) activities may be helpful to eliminating the class imbalances during classification training. If no significant improvement were found after the separating out the static and non-static activities, it might mean further sensor devices or data points maybe required to delineate the different transitioning activities from each other.

Next, I would suggest CNNs, and LSTM RNN's to be used for the Artificial Neural Network.

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