Domain background

The aim of Human Activity Recognition (HAR) is to establish the actions performed by someone given a set of observations about the person and the surrounding environment. This has many uses in healthcare applications, for example monitoring the daily activity of elderly people or the monitoring of activity levels in the overweight and obese[1]. Recognition of activity can be accomplished by retrieving information from various sources such as sensors worn on the body[2,3]. Dedicated motion sensors on different body parts such as the waist, wrist, chest and thighs achieve good classification performance[4], however these sensors are usually uncomfortable and do not provide a long-term solution for activity monitoring[5]. Smartphones (with embedded built-in sensors such as accelerometers and gyroscopes) are an alternative solution for HAR. These devices provide a flexible, affordable and self-contained solution to automatically and unobtrusively monitor Activities of Daily Living (ADL).

The database to be used in this project, the Human Activity Recognition database[6], was created from recording the activities of daily living (ADL) of 30 subjects whose activities were recorded by a waist-mounted smartphone with embedded inertial sensors. The objective of this project is to classify activities recorded in the database into one of six activities (standing, sitting, laying down, walking, walking downstairs and walking upstairs).

I have an undergraduate degree in Exercise and Health Sciences and a Masters in Sports and Exercise Science and therefore have a personal interest in this problem and an understanding of the benefit of accurate activity classification.

Problem Statement

The rapid rise in obesity levels has led to increased clinical and public health interest in effective weight loss programming[10]. The monitoring of physical activity levels using a device has been shown to improve the efficacy and results when following a weight loss programme[11]. The objective of this project is to record the activity levels of subjects using a Samsung Galaxy SII phone and classify activities into one of the six activities performed by processing the recorded data through a Machine Learning (ML) algorithm. This will be done using a Support Vector Machine (SVM) approach which has been used in previous projects to analyse the HAR database[1,6].

Datasets and Inputs

The dataset was collected from 30 subjects aged 19-48 years old who, whilst wearing a Samsung Galaxy SII smartphone on their waist, performed six activities (WALKING,

WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LYING). The accelerometer and gyroscope within the phone were used to capture speed and direction of movement at a constant rate of 50Hz. The experiments were recorded by video and after reviewing the video the data was manually labelled. The dataset was then randomly split into two sets, with 70% of the subjects providing the training data and 30% the test data.
For each record in the dataset, the accelerometer within the phone was used to estimate body acceleration whilst the gyroscope was used to estimate triaxial velocity. There was also an activity label, an identifier of the subject and a 561-feature vector with time and frequency domain variables. In total there are 10299 instances which are currently unbalanced (WALKING = 1226, WALKING_UPSTAIRS = 1073, WALKING_DOWNSTAIRS = 986, SITTING = 1286, STANDING = 1374, LYING = 1407). The classes will be balanced as balanced class distribution gives more accurate and fair results [12].

Solution Statement

It is proposed that a SVM approach (more specifically a multi-class SVM) is used to analyse the data. This approach has been shown to perform well in similar studies, such as a study by Karantonis et al [7]. where a system provided an accuracy of 90.8% using data collected from 6 volunteers for the classification of 12 ADL using a waist-mounted triaxial accelerometer. A similar study [8] obtained a recognition performance of 93.9% used a chest-mounted accelerometer to classify 5 ADL. As there are over 500 features in the dataset a data reduction technique, Principal Component Analysis, will be used to compress the dataset. As an SVM is being used, the data will be scaled using the min-max scaler which will translate each feature so that it is within a given range.

Benchmark model

The data will be trained and tested on a random forest classifier using the sklearn.ensemble.RandomForestClassifier package from scikit-learn. When the final solution has been applied to the data, the results can then be compared to the random forest model (the benchmark model) so an objective comparison can be made to see if the benchmark model is outperformed.

There are a number of studies that have used the ADL dataset and have shown an accuracy of 90-96%. The benchmark to be compared against in this project will be taken from the the paper by et Anguits et al[9]. This study showed an overall accuracy of 96% for the test data composed of 2497 patterns. This may be used as a secondary benchmark model.

Evaluation metrics

There are two types of predictive models, the regression model (continuous output) or a classification model (nominal or binary output). A mathematical metric, log loss, will be used as an evaluation metric. Log Loss measures the accuracy of a classification model by giving a probability value of between 1 and 0 for a predicted value. The better the machine model is, the lower the probability value will be with the perfect model having a log loss of 0. A confusion matrix allows visualization of the performance of an algorithm of a classification problem in the form of a table and is used to show how classification model is confused when it makes predictions. Each row of the matrix corresponds to a predicted class while each column of the matrix corresponds to an actual class (or vice versa). This project is a classification problem and it is suggested that, in a similar way to Anguita et al[6], a confusion matrix will be used as a supporting evaluation metric.

A confusion matrix takes the form of an N X N matrix, where N is the number of classes being predicted. For the problem in this project, N=6, and therefore will be a 6 X 6 matrix as is shown below.

	WK	WU	WD	ST	SD	LD	**Recall (%)**
WK							
WU							
WD							
ST							
SD							
LD							
Precision (%)							

Walking = WK, Walking upstairs = WU, Walking downstairs = WD, Sitting = SD, Standing = SD, Lying down = LD

The table above will be filled in when the project is run to visualise the results.

Project design

At a high level, the workflow of the project will involve the loading of the dataset, the preprocessing of the data, model generation, and finally the evaluation and optimisation of the results. The sklearn.preprocessing package from scikit-learn will be used to preprocess the data. This project will use a SVM classifier which has been used previously with the HAR dataset [1,6]. A confusion matrix will be used to evaluate the results.

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