Human Activity Recognition

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***Abstract*—Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat.**

***Index Terms*—Human activity, Classification, Deep learning**

I. Introduction

Human Activity

II. Background Research

A. Smartphone Accelerometers

B. Support Vector Machines

Support Vector Machines (or SVMs) are a type of classifier used for classification and regression. SVM seeks to classify samples as different classes on a hyperplane in multidimensional space. The classification process generates multiple hyperplanes to find the one which minimises an error value. Generally, support vector machines are used for binary classification problems. However, they can be adapted to multiclass problems by converting or reducing them into a set of multiple binary classification problems. However some samples cannot be classified linearly, hence SVMs can also make use of kernels to transform non-linear space into linear space, which was proposed by Boser et al. [1].

C. Convolutional Neural Networks

III. Literature Review

Anguit et al. [2] classified activities into two different categories: static and dynamic activities. Using a One-Vs-All approach and a Laplacian kernel, they obtained highly accurate rates of classification. Demrozi et al. [3] compiled a number of studies on human activity recognition (Human Activity Recognition using Inertial, Physiological and Environmental Sensors: A Comprehensive Survey) and found that out of 149 papers published between January 2015 and September 2019, 53 examined deep learning models and the remaining 96 were classical machine learning models.

Statistical Measure	Description
mean	Mean value in the window
min	Smallest value in the window
max	Largest value in the window
std	Standard deviation
entropy	Entropy
mad	3
iqr	Inter-quartile Range
energy	3
sma	Signal magnitude area
arCoeff	3
correlation	3
angle	Angle between 2 vectors of signals
band energy	3

TABLE I
TABLE 1

Statistical Measure	Description
maxInds	1
skewness	2
kurtosis	3
meanFreq	3

TABLE II
TABLE 2

IV. Design and Methodology

A. Feature Extraction

Excluding the label for each activity, each session in the dataset contains 589 features. These features were extracted by applying a number of different statistical measures to the different extracted signals in each sliding window.

Each signal has the following statistical measures applied to them.

The following statistical measures are applied only to FFT signals

B. Signal Processing

C. Support Vector Classifier

1) Data Pre-processing:

2) Comparing different classification models: In total, four different classic machine learning classifiers were used on the dataset developed by Anguita et al [2]. These classifiers are Gaussian Naïve Bayes, AdaBoost, Stochastic Gradient Descent and a Support Vector Classifier. These were trained and tested using the respective datasets, and their accuracy, F-beta, precision and recall scores were recorded.

D. Classification

V. Evaluation

Figure 1 above is the confusion matrix representing the accuracy of the classification of each activity as a percentage. The leading diagonal represents correctly labelled activities. Each activity group classified had an accuracy of 96% or higher, with half activities being classified at an accuracy of 99-100%. 1% of driving activities were misclassified as sitting. This was to be expected as during driving sessions there were times (i.e. being stuck in traffic) where the driver was stationary and in the same position as that of someone seated down. 2% of laying activities were misclassified as sitting, this is understandable as the two stationary activities have similar positions.

VI. Conclusion and Future Work

The purpose of this report is to discuss the problem, view the existing solutions and to present the work that has been done to date mainly the automatic user profiling prototype. Further development regarding both the improvement of such a prototype and the development of the automatic itinerary generation will take place in the upcoming weeks.

VII. Distribution of Work

- Jake Sant
- Aiden Williams
- Ethan Zammit

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