Determining Individual Characteristics from Human Activity Data (iPhone Motion Sensor)

Introduction

Ofcom's figures indicate that in 2020 45 percent of households in the UK had two mobile phones. Published figures indicate there were over 53 million smartphones in the UK in May 2021 and over 2,700 million globally (O'Dea, 2021). It is therefore important to understand how smartphone data could be used, or abused. How could our privacy be impacted? The question I am interested in answering is - Can activity data recorded on a smartphone be used to infer individual characteristics about user, weight, height, gender, age, and if so, to what degree of accuracy?

Related Work

Research studies have established it is possible to recognise the type of activity that the user is undertaking to a high degree of accuracy. Researchers from University of California, Irving undertook experiments with a group of 30 volunteers within an age bracket of 19-48 years. The dataset is publicly available and has been used as a data source for many research papers (Reyes-Ortiz, 2012). Each person performed six activities wearing a smartphone (Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, linear acceleration and angular velocity was captured at a constant rate of 50Hz.

On this similar dataset, support vector machine classifier and convolutional neural network machine learning models achieved almost 100 percent accuracy when determining activity type (Sun, 2019). Analysis established that within a short amount of time (1-1.5 min) the smartphone has enough data to determine what its user is doing (95%: 6 activities) or who the user is (Walking 94%: 30 participants) and even the basics of a person's specific walking style (Liftoff, 2019).

There is some existing analysis of this dataset published on GitHub and Kaggle websites. There is an initial exploratory analysis of the data subjects who participated in the trials (Shaar, 2019). There is also an example of predicting gender and average weight using this dataset (Huang, 2019). I build on both these pieces of work. There is also published analysis of this time series data (Malekzadeh, 2019).

Broader context

Cardiac abnormalities are one of the leading causes of deaths all over the globe. Smartphone-based systems may offer opportunities for real-time cardiac monitoring and early abnormality detection (Shabaan et. al, 2020). It is important to test the accuracy of predictive models utilising smartphone data.

A paper on wearable devices identified 423 unique devices from 132 different brands. With recent advances in mobile sensor technology, privately collected physical activity data can be used as an addition to existing methods for health data collection in research (Henriksen et. al, 2018). Given the popularity of wearable mobile sensors, it is important to determine whether smartphone activity data could provide a viable alternative.

If users can be personally identified by smartphone motion data the implications are that sensor data could be biographically significant legally, under the General Data Protection Regulations (Liftoff, 2019). Therefore data privacy concerns need to be addressed when data 'relates to or is 'obviously about' a particular individual. It is important that smartphone users understand the data that can be captured. This will allow informed choices to be made and privacy trade-offs to be transparent. Users may find monitoring useful for improving the quality health interventions.

Hypothesis

The hypothesis being assessed is whether personal characteristics of weight, height, age and gender can be predicted from motion sensor captured by a smartphone. The analysis evaluates a series of machine learning classifiers.

Experiment

An experiment at Queen Mary University of London generated the dataset being reviewed. Time-series data was generated by accelerometer and gyroscope sensors. It was collected from an iPhone 6s kept in the participants' front pocket using SensingKit which collects information from Core Motion framework on iOS devices. All data collected in 50Hz sample rate. A total of 24 participants in a range of gender, age, weight, and height performed 6 activities in 15 trials, of varying length, in the same environment and conditions: downstairs, upstairs, walking, jogging, sitting, and standing. Full study conditions are provided by the researchers to allow repetition (Malekzadeh, 2019).

Modelling

Regression is an algorithm in supervised machine learning that can be trained to predict real number outputs. In this analysis I was interested in whether or not the individual could be identified as above or below average height, weight and age, not what the actual value was. Gender was only recorded as male or female, therefore I used classifiers. Classification is an algorithm in supervised machine learning that is trained to identify categories and predict in which category they fall for new values. The most common way to measure the accuracy of a classification model is by simply calculating the percentage of correct classifications the model makes on test data, after being trained on a training data set.

If there exists a hyperplane that perfectly separates the two classes, then the two classes linearly separable. Few examples of linear classifiers are Logistic Regression, Perceptron, Naive Bayes, Support Vector Machines, etc. Examples of non-linear classifiers are Decision Trees, K-Nearest Neighbour, Random Forest, non-linear-kernel Support Vector Machines, etc. K-Nearest Neighbour uses variable distance, Euclidean is most popular calculation used. This classifier is better for small data.

Logistic Regression is shallow learning (linear), Multi-Layer Perceptron is deep (non-linear). Deep learning refers to neural networks with multiple hidden layers that can learn increasingly abstract representations of the input data.

Multi Layer Perceptron (more than one layer) is suitable for non-linear separable data. However it is difficult to see relationship between input and output and may not scale well. A multilayer perceptron (MLP) is a class of feedforward artificial neural network (ANN). An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a non-linear activation function. MLP utilises a supervised learning technique called backpropagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable.

Summary of analysis

Following the CRISP-DM methodology, I researched the dataset to understand context and reviewed existing analysis. I performed exploratory data analysis and generated numerical and graphical summaries to understand the data associated to the trial participants.

There were 24 data subjects in the trial, 10 were females and 14 males. The raw data from the 15 activities conducted by the 24 participants was loaded and grouped into the 6 activities. Exploratory analysis was conducted to ascertain spread of height, weight, gender, age for the trial participants as a group, and then subdivided by gender. A histogram, correlation matrix and scatter plot was generated for the whole group, then for males and females. Minimum, maximum and mean values were calculated for each attribute for the whole group, then for males and females.

I based my exploratory analysis of trail participants on the work performed by Shaar (Shaar, 2019). I reused and extended his work by cleansing the data to move code, which was a unique identifier and didn't add value to the analysis. I generated additional graphs splitting the data by gender, histogram/bar chart, correlation matrix and scatter/density plots. In addition, I produced a summary tables for minimum, maximum, average variable values for the whole dataset and also by gender.

For the trial output data, I added labels to allow opportunities to use supervised learning as well as unsupervised machine learning models and techniques. I cleansed, grouped, filtered, performed feature engineering and scaled the data in preparation. I performed mapping for trial participants to determine whether they were over average weight, height and age (setting the response variable to 1 for above, 0 for below). I ran a series of linear and non-linear, machine and deep learning models and evaluated them using a variety of metrics – accuracy, f1 score, time to compile. I produced a confusion matrix for the best performing model, showing error rate for true and false, positive and negative predictions.

The multivariate time-series has 12 features: attitude.roll, attitude.pitch, attitude.yaw, gravity.x, gravity.y, gravity.z, rotationRate.x, rotationRate.y, rotationRate.z, userAcceleration.x, userAcceleration.y, userAcceleration.z. The data was loaded with added identifiers for the experiment number, participant number and activity type. Exploratory analysis was conducted to ascertain class balance, hierarchical clustering and a sample of the timeseries data (userAcceleration.x) was examined by activity type. In total there were over 1.4m observations with 16 attributes. The datasets for the downstairs and jog were the smallest data sets, upstairs and standing next in order, with sitting and walking datasets the largest. I chose not to balance the data, preferring to use a subset of activity type data or the whole dataset.

Best Subset Selection analysis was conducted on the whole dataset, using a Logistic Regression model. I repeated the Best Subset Selection analysis using two subsets of the data, on the Jogging activity type and on the Standing activity type. I evaluated the output using first RSS and R squared then Mallow's Cp (C_p), Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC)and Adjusted R2.

I was able to run a limited selection of classification models on subsets of the data, split by activity type. I did scale the data, which improved the accuracy of the models. I did not apply feature engineering at this stage. I ran two Logistic Regression models, Decision tree and K-Nearest Neighbour against Jogging, Standing. Then I grouped activity types that indicated movement, 'Move' is the analysis consisting of Upstairs, Downstairs, Walking trials and no movement named 'Static' in the analysis, consisting of the trial results for Standing and Sitting activity types. I used the models to predict the trial participant, and then if gender or above and below weight, age, height could be predicted. In addition to accuracy I tracked how long each model took to compute on Google Colab.

I extended the work produced by Y.C. Huang (Huang, 2019). I utilised his approach to feature construction and engineering based on that of ROYT's (T, 2019) allowing use of all complete dataset. In addition to gender and weight prediction I extended Huang's work to include mapping for height and age. I split the data to allow for training and testing of eight classifiers. I scaled the training data and applied a variety of linear and non-linear deep and machine learning models – Multi Layer Perceptron, Support Vector Machine Linear, Support Vector Machine - Radial Basis Function (RBF), Logistic Regression (L1), Logistic Regression (L2), Decision tree, Random Forest, K- Nearest Neighbour.

The response variable was adjusted to determine model accuracy for predicting activity type, trail participant and activity type, trial participant, gender, weight, height and age. In addition to model accuracy scores, mean f1 score values were produced and a confusion matrix was generated for the best performing model. Analysis of the importance of attributes was also conducted for the most accurate model being Random Forest.

In addition, I also ran seven of the models against the time-series data with a sliding window algorithm. I performed channel-normalisation and scaling. I reused code developed by Mohammad Malekzadeh and Adam Martin (Malekzadeh, 2019) to load the data. I reused and adapted the sliding window and feature engineering code from Yu Guan (Guan, 2019).

Results & Conclusion

Even when the limitations of the dataset are considered, it is reasonable to conclude that personal characteristics of weight, height, age and gender can be predicted to a high degree of accuracy when using machine learning models to evaluate human activity sensor data. Scaling the data improves model accuracy

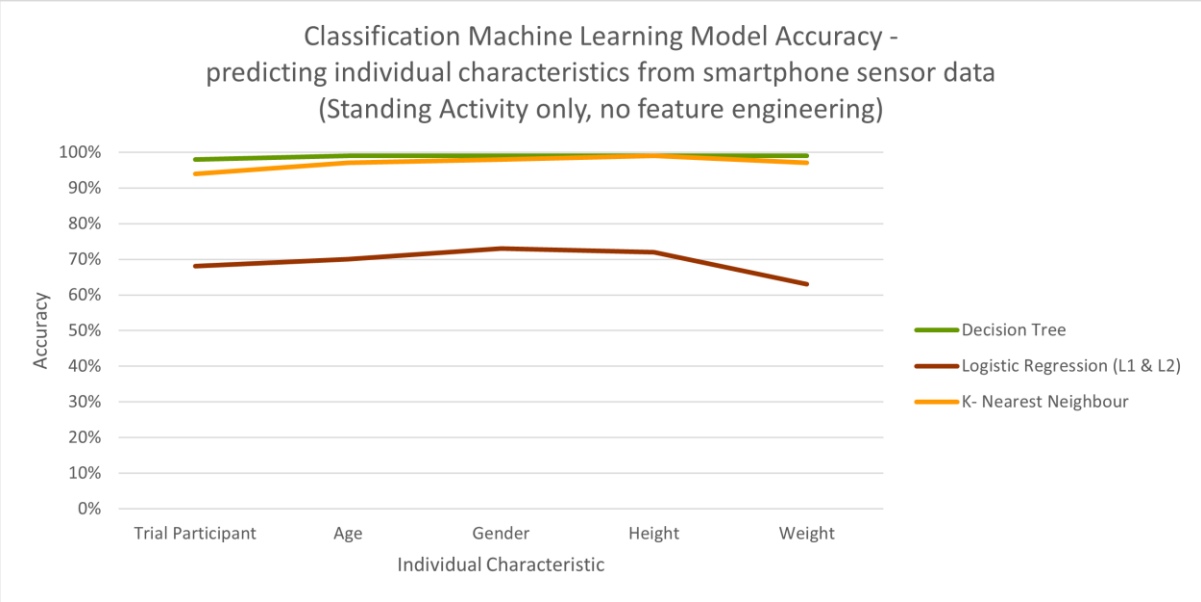
marginally but applying feature engineering significantly improves the computational speeds and accuracy rates.

The sample size of trial participants was small with less than 30. If the sample size is too small it may be difficult to detect what was intended (Kar & Ramalingam, 2013). The trial participants, and therefore the information gathered may not be reflective of the population, i.e. the speed of movements within younger individuals may not be reflective of an older population. Therefore any predictions on age, gender, weight or height, given the small sample may not be an accurate prediction of test error.

Scaled data, no feature engineering

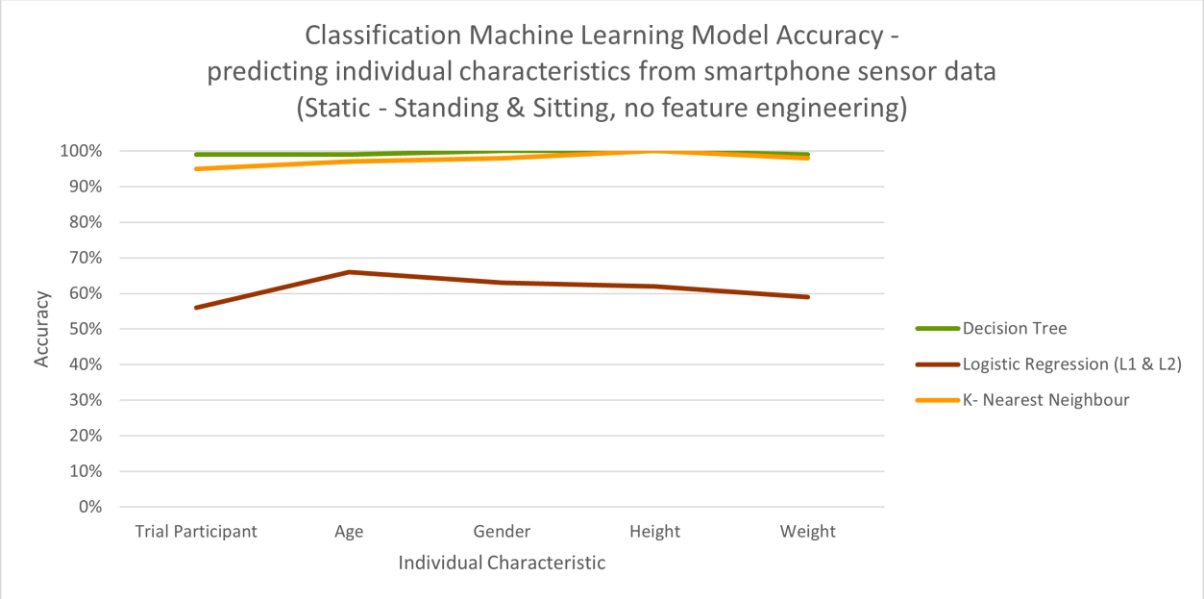
Standing - Performance of the models varied significantly with the Decision Tree Classification Model marginally more accurate than K- Nearest Neighbour, having the highest accuracy for each variable. Models ranged in accuracy of predicting gender 73% to 99%, height 72% to 99%, age 70% to 99% and weight from 63% to 99% accuracy.

Model Evaluation - Standing	Trial Participant			Age			Gender			Height			Weight			Average		
	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute
Decision Tree	98%	98%	19.1	99%	99%	7.75	99%	99%	7.1	99%	99%	6.7	99%	99%	7.06	99%	99%	9.54
Logistic Regression (L1)	68%	67%	41	70%	69%	0.84	73%	72%	1.08	72%	72%	3.78	63%	61%	1.22	69%	68%	9.58
Logistic Regression (L2)	68%	67%	41	70%	69%	0.87	73%	72%	1.07	73%	72%	3.94	63%	61%	1.19	69%	68%	9.61
K- Nearest Neighbour	94%	94%	93.96	97%	97%	94.09	98%	98%	89.12	99%	99%	14.95	97%	97%	89.41	97%	97%	76.31
Average	82%	82%	48.77	84%	84%	25.89	86%	85%	24.59	86%	86%	7.34	81%	80%	24.72	84%	83%	26.26



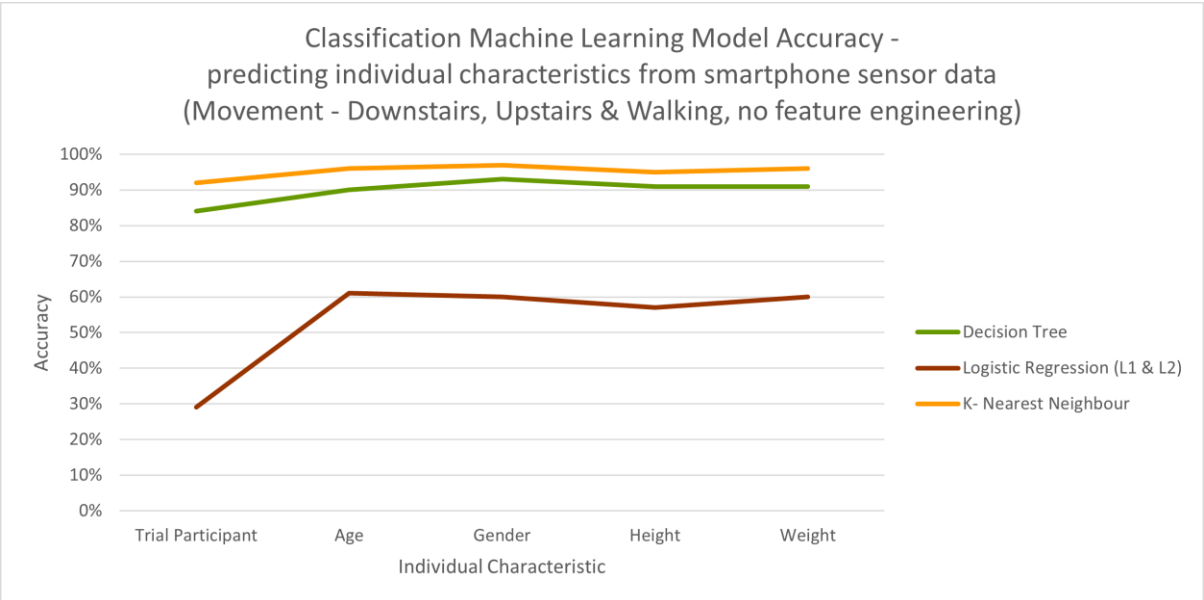
Static (Standing & Sitting) - Performance of the models varied significantly with the Decision Tree Classification Model having the highest accuracy for each variable. Time to compute also varied vastly, with the Logistic Regression Models completing fastest but having lowest accuracy. Models ranged in accuracy of predicting gender 63% to 100%, height 62% to 100%, age 66% to 99% and weight from 59% to 99% accuracy.

Model - Static (Sitting & Standing) Evaluation	Trial Participant			Age			Gender			Height			Weight			Average		
	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute
Decision Tree	99%	99%	33.78	99%	99%	15.94	100%	100%	13.41	100%	100%	14.45	99%	99%	15.8	99%	99%	18.68
Logistic Regression (L1)	56%	53%	84.57	66%	65%	1.87	63%	61%	1.94	62%	61%	8.5	59%	54%	1.85	61%	59%	19.75
Logistic Regression (L2)	56%	53%	82.83	66%	65%	1.88	63%	61%	1.87	62%	61%	8.52	59%	54%	1.8	61%	59%	19.38
K- Nearest Neighbour	95%	95%	200.67	97%	97%	242.39	98%	98%	231.73	100%	100%	52.29	98%	98%	229.91	98%	98%	191.40
Average	77%	75%	100.46	82%	82%	65.52	81%	80%	62.24	81%	81%	20.94	79%	76%	62.34	80%	79%	62.30



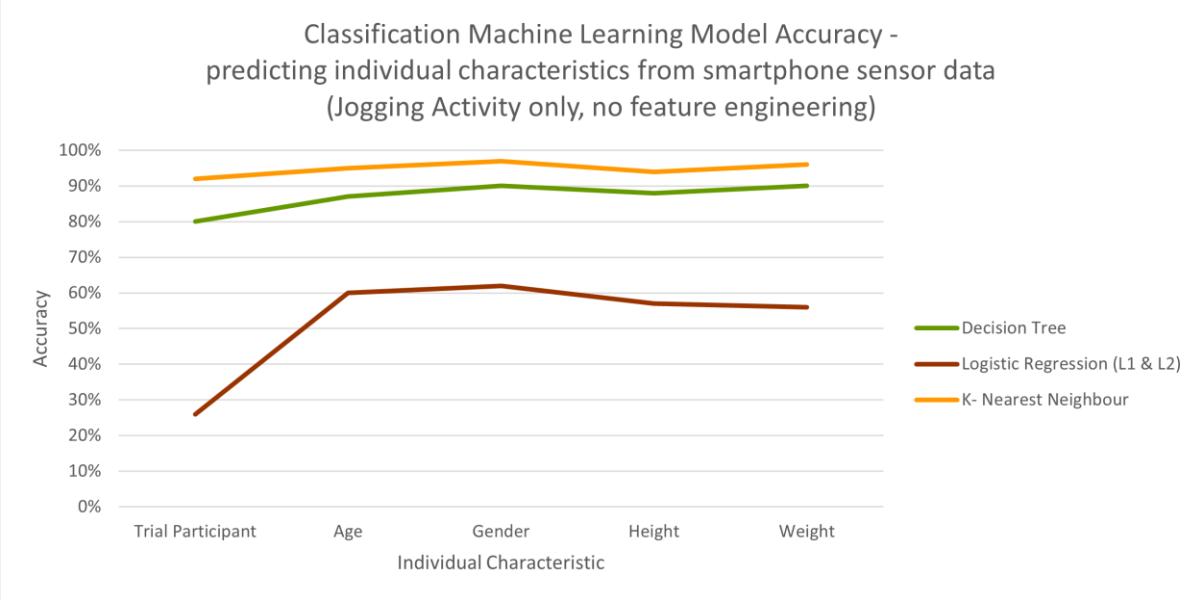
Move (Upstairs, Downstairs, Walking) - Performance of the models varied significantly with the K- Nearest Neighbour Classification Model having the highest accuracy for each variable. Time to compute also varied vastly, with the Logistic Regression Models completing fastest but having lowest accuracy. Models ranged in accuracy of predicting gender 60% to 97%, height 57% to 195%, age 61% to 96% and weight from 60% to 96% accuracy.

Model Evaluation - Move (Upstairs, Downstairs, Walking)	Trial Participant			Age			Gender			Height			Weight			Average		
	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute
Decision Tree	84%	84%	105.85	90%	90%	41.08	93%	92%	35.27	91%	91%	38.38	91%	91%	37.74	90%	90%	51.66
Logistic Regression (L1)	29%	24%	98.54	61%	57%	2.44	60%	55%	2.59	57%	56%	6.33	60%	51%	2.4	53%	49%	22.46
Logistic Regression (L2)	29%	24%	103.75	61%	57%	2.43	60%	59%	2.58	57%	56%	6.4	60%	51%	2.39	53%	49%	23.51
K- Nearest Neighbour	92%	92%	297.98	96%	96%	367.95	97%	97%	390.19	95%	95%	158.77	96%	96%	360.62	95%	95%	315.10
Average	59%	56%	151.53	77%	75%	103.48	78%	76%	107.66	75%	75%	52.47	77%	72%	100.79	73%	71%	103.18



Jogging - Performance of the models varied significantly with the K- Nearest Neighbour having the highest accuracy for each variable. Models ranged in accuracy of predicting gender 62% to 97%, height 57% to 94%, age 60% to 95% and weight from 56% to 96% accuracy.

Model Evaluation - Jogging	Trial Participant			Age			Gender			Height			Weight			Average		
	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute
Decision Tree	80%	79%	14.85	87%	87%	4.88	90%	90%	4.86	88%	88%	5.12	90%	89%	4.59	87%	87%	6.86
Logistic Regression (L1)	26%	22%	20.95	60%	55%	0.38	62%	56%	0.38	57%	55%	1.23	56%	45%	0.42	52%	47%	4.67
Logistic Regression (L2)	26%	22%	20.73	60%	55%	0.39	62%	56%	0.38	57%	55%	1.22	56%	45%	0.38	52%	47%	4.62
K- Nearest Neighbour	92%	91%	23.35	95%	95%	24.99	97%	97%	24.04	94%	94%	16.54	96%	96%	24.24	95%	95%	22.63
Average	56%	54%	19.97	76%	73%	7.66	78%	75%	7.42	74%	73%	6.03	75%	69%	7.41	72%	69%	9.70



Feature engineering on scaled data

Performance of the models varied significantly with the Random Forest Classifier having the highest accuracy for each variable. Models ranged in accuracy of predicting gender 70% to 97%, height 62% to 97%, age 63% to 94% and weight from 61% to 96% accuracy.

Model Evaluation	Trial Participant			Age			Gender			Height			Weight		
	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute	Accuracy	mean f1 score	Secs to compute
Random Forest	95%	95%	85.39	94%	94%	25.13	97%	97%	23.02	97%	97%	24.26	96%	96%	27.55
Multi Layer Perceptron	86%		0.11	89%		0.11	91%		0.12	87%		0.11	88%		0.11
Decision Tree	77%	77%	1.13	86%	86%	0.33	93%	93%	0.29	89%	89%	0.27	88%	88%	0.35
Logistic Regression (L1)	76%	76%	0.8	72%	71%	0.11	79%	79%	0.14	73%	73%	0.13	73%	71%	0.11
Logistic Regression (L2)	76%	76%	0.81	72%	71%	0.15	79%	79%	0.14	74%	73%	0.14	74%	71%	0.12
K- Nearest Neighbour	75%	75%	0.27	87%	87%	0.26	90%	90%	0.26	88%	88%	0.27	87%	87%	0.27
SVM RBF	63%	63%	1.22	69%	68%	0.9	75%	74%	0.73	71%	71%	0.9	70%	66%	0.85
SVM Linear	25%	21%	0.94	63%	57%	0.52	70%	70%	0.48	62%	62%	0.62	61%	47%	0.51

Table 1 – Model Performance

The Random Forest classification model consistently performed with highest accuracy for predicting trial participant, age, gender, height and weight. The Support Vector Machine Linear model consistently performed with lowest accuracy, indicating that the data was non-linear.

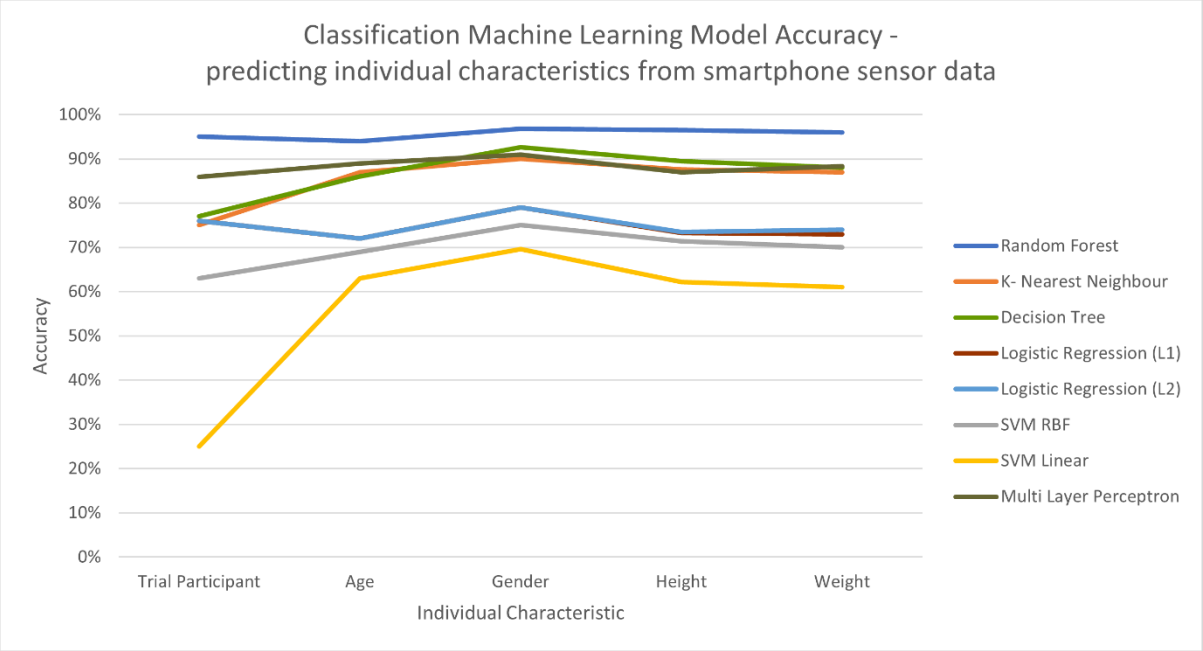


Figure 1 – Model Evaluation (Accuracy)

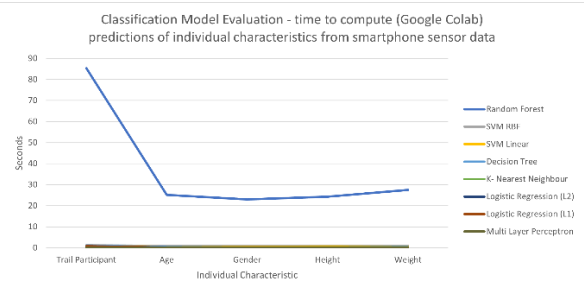


Figure 2 – Model Evaluation (Speed – All Models)

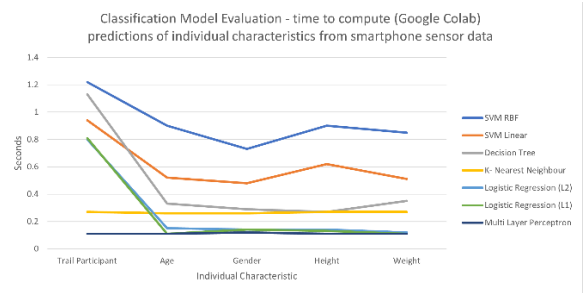
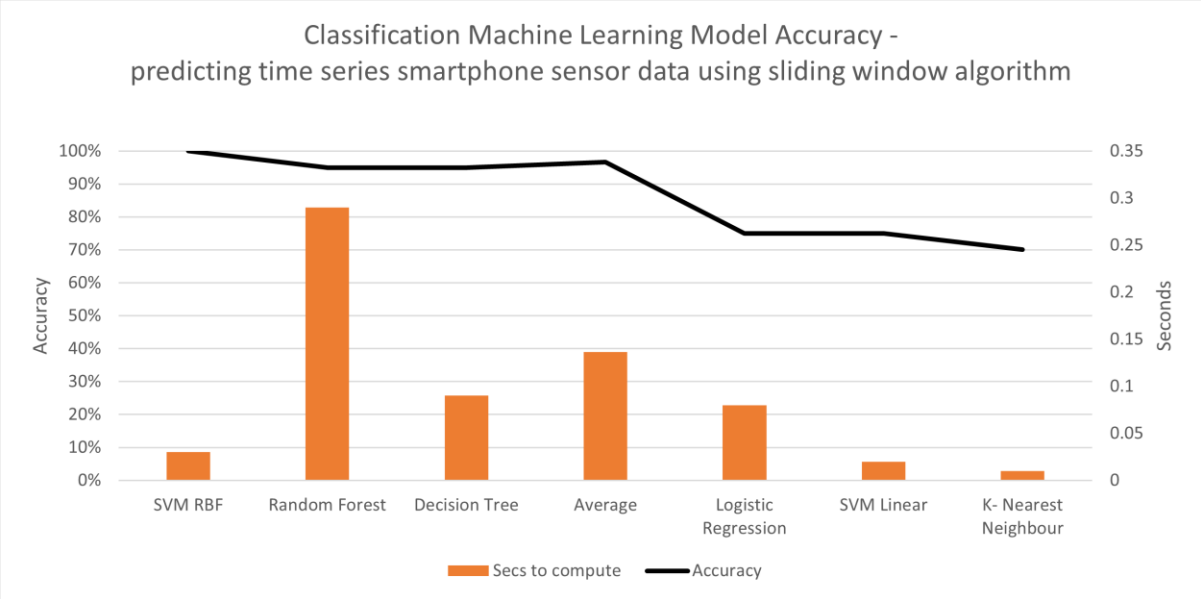


Figure 3 – Model Evaluation (Speed - Fastest Models)

Time series, feature engineering, sliding window

On the time series, I ran a sliding window algorithm. The Random Forest model had the highest accuracy at 95% and also took the longest time to compute, 0.29 seconds. The lowest accuracy was 70% from K-Nearest Neighbour with a total computational time of 0.01 seconds.

Model Evaluation - Sliding Window	Accuracy	mean f1 score	Secs to compute
SVM RBF	100%	100%	0.03
Random Forest	95%	95%	0.29
Decision Tree	95%	95%	0.09
Average	97%	97%	0.14
Logistic Regression	75%	67%	0.08
SVM Linear	75%	67%	0.02
K- Nearest Neighbour	70%	57%	0.01



Evaluate success

Feature engineering did seem to have an effect on model performance with the rank order changing depending on the encoding technique applied to the raw data.

The Random Forest model performed better than the Decision Tree model, this is possibly due to the dimensionality of the data being high and decision boundary being smooth. Decision tree models can easily overfit, cope poorly with high-dimensionality data and have a block effect to decision boundaries.

Scaling the data improved the accuracy of the models. Due the high dimensionality of the data set is was necessary to apply feature engineering if using the whole dataset. I was able to run Best Subset Selection analysis on the whole dataset using Logistic Regression. However the results of the Best Subset Selection analysis didn't allow reduction of the dataset as all variables were required. Google Colab resources would not permit me to undertake the Best Subset Selection analysis using other models.

The calculated mean f1 score did not vary significantly with the exception of Support Vector Machines prediction for weight on the dataset where I performed feature engineering.

Future implications

Due to the similarities in activity types, the data could have been grouped into three subsets – 1) downstairs, upstairs and walk 2) sitting and standing 3) jogging. It is expected that model accuracy would have been improved even further.

The number of participants and the diversity of weight, height, age and gender could have been increased. This would improve the quality of the analysis, modelling and any conclusions.

Feature engineering development requires domain knowledge of the data, which I didn't have. More work could be undertaken in this area. The models I produced were based on the feature engineering from Y.C. Huang's code (Huang, 2019), who reused a calculation produced by ROYT (T, 2019). I also reused human activity recognition feature engineering code from Yu Guan (Guan, 2019).

Google Colab resources limited the analysis feasible within a reasonable timescale. Feature engineering was required to allow the models to run efficiently on the complete dataset. Additional computation resources would be needed to analyse the complete dataset without dimension reduction.

Reflections

The process, technologies and methodologies I used involved a mixture of new and previously used. All of the approaches were still new to me. Being honest this assignment, like all the others, has been challenging and rewarding. Even reminding myself how to run the GitLog file took time and persistence. Figuring 'stuff' out on my own and being resilient has its rewards but feels uncomfortable and difficult. In terms of personal and professional development I really enjoy, and hate, the learning process. I struggle being out of my comfort zone, feeling very anxious, stressed and frustrated at times. I need time to absorb information and be able to gain confidence in the topics being taught. Therefore managing my time well has been very important.

Developing trusted relationships with other students has been very useful particularly in determining if I've understood the material in the way that was intended, or at least they understood it. Appreciating that others have a different learning approach has also been valuable and quite insightful. Our differences as humans make us unique and recognising there are more than several 'right' ways has been eye-opening. In future I'd like to think I will be more flexible with how I define tasks for my team to allow them more scope for personal style. When planning learning and development tasks in future I will make sure to allow sufficient time for information to be assimilated, whether for myself or others.

Following feedback from previous assignments, I took more time to follow the Scientific Method and used that format for my report. I attempted to be clearer on how I had identified the problem, approached it, defined it, then selected to model it, evaluate how successful this had been and conclude what future work could be undertaken. I took more time, and words, to explain the rationale for my decisions.

I used the CRISP-DM best practice methodology. The lifecycle contains six phases; Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, Deployment. The process allows for iteration between stages and I did move between data preparation, modelling and evaluation extensively. This lead to a bit of yo-yo-ing. The analysis could have absorbed as much time as I was prepared to give. During the development of my report I cut back the content significantly to ensure it was focused.

I created a GitHub repository using the cookiecutter Data Science template in GitHub. I used Git for version control. I developed models using Python on Google Colab with data stored on Google Drive. The cookiecutter folder structure was useful for organisation and keeping order of my work. Google Colab provided easy access to sklearn library, keras and tensorflow code. I was not able to set up RStudio locally with the Python extensions and 'reiterate' library using a virtual environment.

I enjoyed learning Python and the Save As and Find and Replace features within Google Colab were extremely useful. Google Colab resources had limitations and signing on to the Google drive for each notebook felt unnecessary. The dataset needed dimensional reduction to run all the models within reasonable timescales. I needed to split the code into separate notebooks to keep the size of the Python notebooks manageable. Uploading files directly from Google Colab needed the GitHub repository to be set to 'public'. Change of access and visibility needs password approval and additional text so switching this on and off was fiddly, although not difficult. As a result I limited my commits to when there was a reasonable amount of work to update within the repository. I would recommend Google Colab based on my experience. Although I had not coded before in Python, I did find it reasonably intuitive but handling code errors in Jupyter notebooks was not as easily identifiable or rectifiable as R. Some tasks were beyond my skillset and I had to accept defeat. There were some sections of code I was unable to generate due to library problems in Google Colab (dtiadistance gave a C language error, for example).

The two Logistic Regression Models produced very similar results and I possibly could have removed one had I realised that early enough. It was only in the final review I realised how similar they were.

Detailed findings

There were 24 data subjects in the trial, with average weight of 72kg (11 stones 4lb), average age of 29 and average height of 174cm (5ft 8.5') Fourteen males and ten females participated.

The histograms for the data show the variation in weight, height, age and gender of the participants in the trail. The average weight of all trail participants was 72.125kg, average height was 174.2cm and average age of 28.79 years. Fourteen males and ten females participated.

Average age of the female participants was 26.2 years, average height was 166.8cm and average weight was 65.2kg. Average age of the male participants was 30.6 years, average height was 179.5cm and average weight was 77.0kg.

The oldest, heaviest and tallest participants in the trial are males. The lightest, smallest and youngest are all female participants. There is a correlation between height and weight and a weaker correlation between age and weight for female participants. for male participants, the only and strongest correlation is between height and weight.

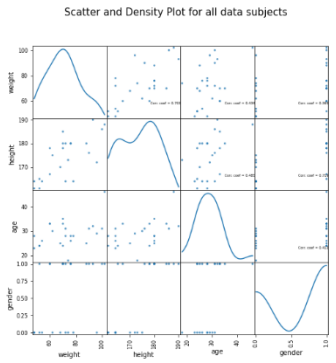


Figure 6 – Scatter Plot (All Trial Participants)

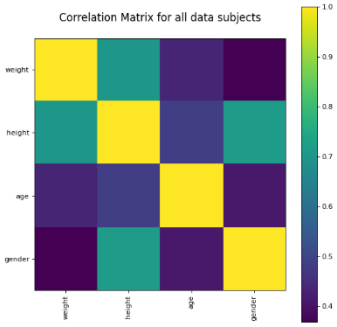


Figure 7 – Correlation Matrix (All Trial Participants)

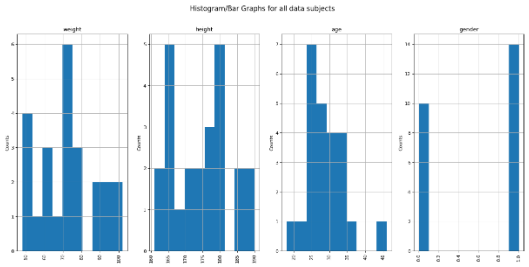


Figure 8 – Histogram (All Trial Participants)

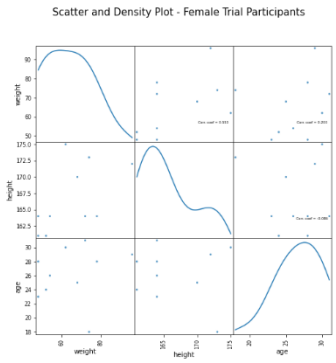


Figure 9 – Scatter Plot (Female Participants)

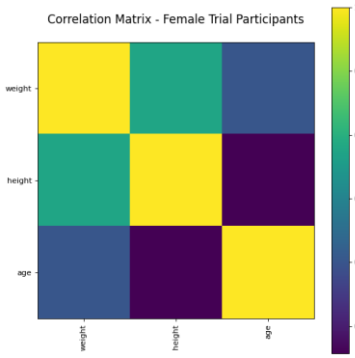


Figure 10 – Correlation Matrix (Female Participants)

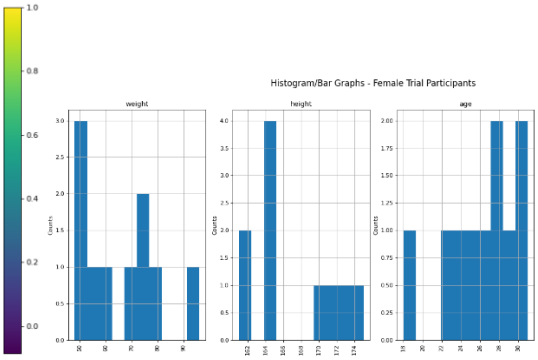


Figure 11 – Histogram (Female Participants)

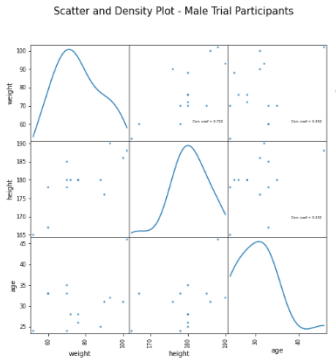


Figure 12 – Scatter Plot (Male Participants)

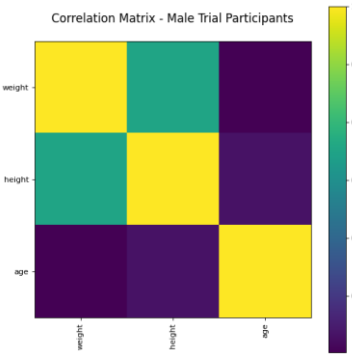


Figure 13 – Correlation Matrix (Male Participants)

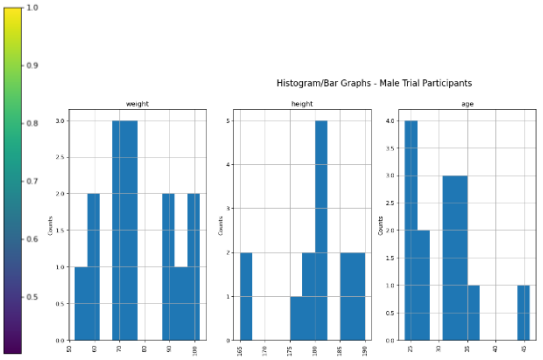


Figure 14 – Histogram (Male Participants)

Best Subset Selection analysis was conducted on the whole dataset to determine the variables required to accurately predict activity type, i.e. which variables accounted for the highest variance. A further two subsets of the data where activity type was known, Jogging and Standing were analysed to determine the

variable required to accurately predict trial participant. All the Best Subset Analysis was undertaken without scaling or feature engineering, using a Logistic Regression model. Due to the high number of recommended predicter variables there was little opportunity to reduce the dataset.

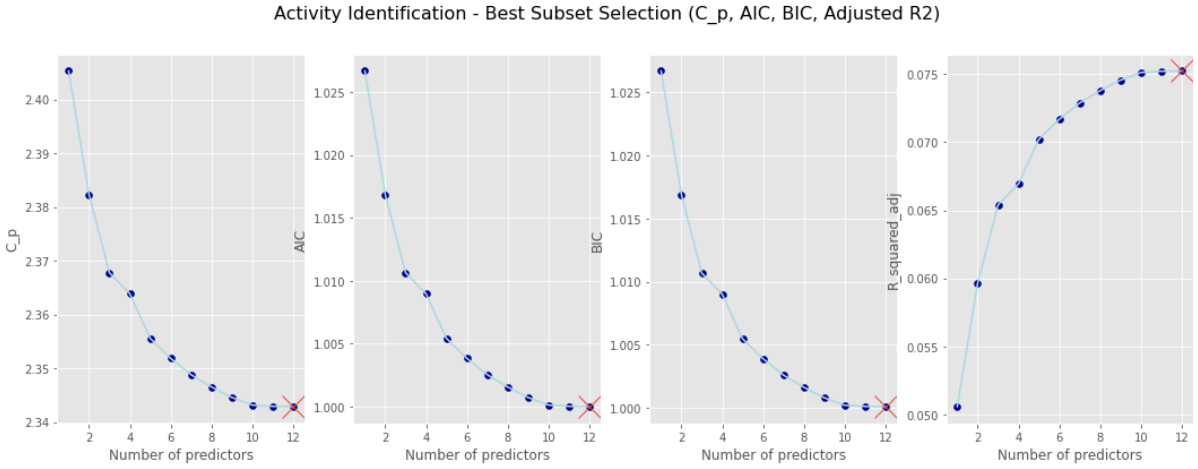


Figure 15 – Best Subset Selection Evaluation (All Data)

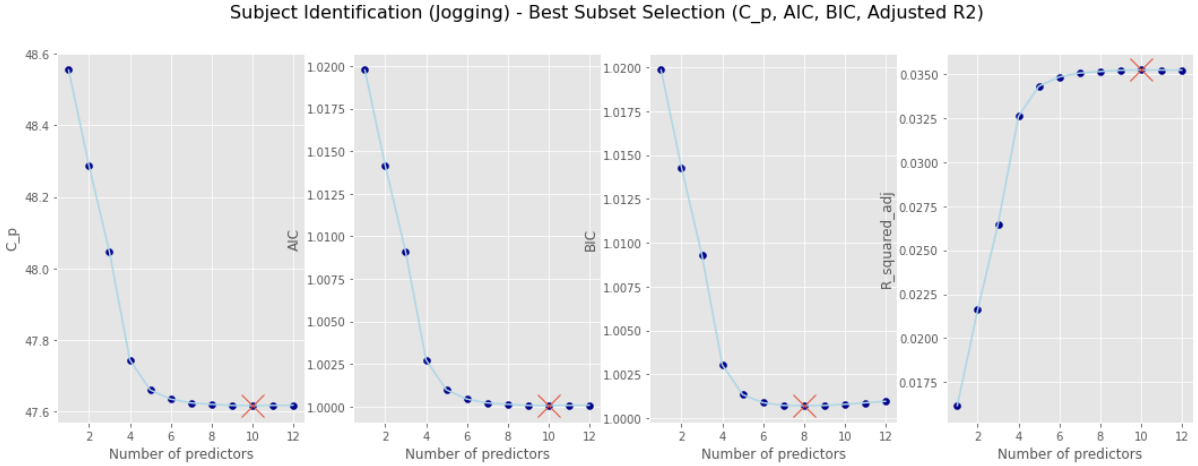


Figure 16 – Best Subset Selection Evaluation (Jogging Activity Type)

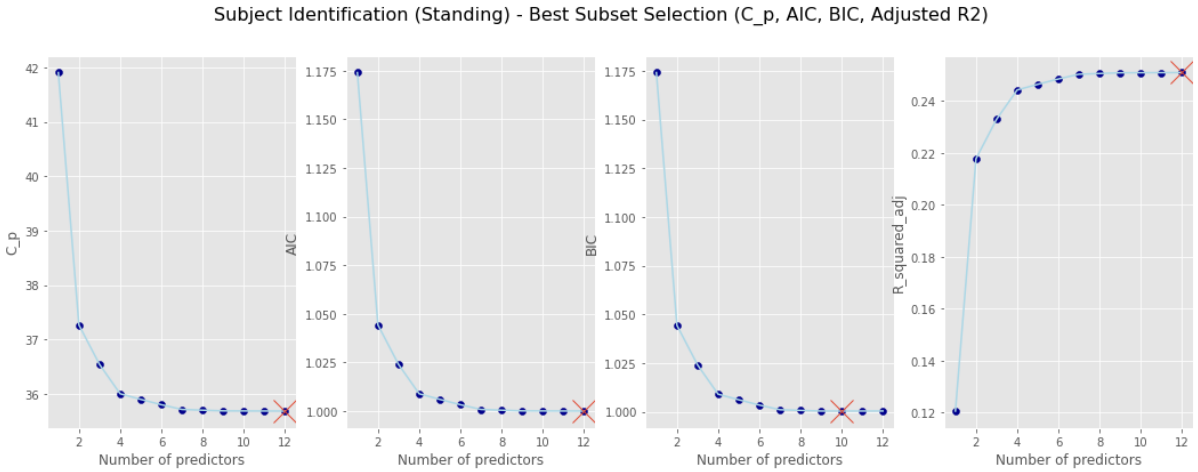


Figure 17 – Best Subset Selection Evaluation (Jogging Activity Type)

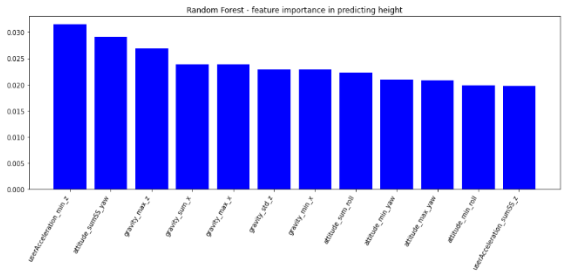


Figure 6 – Feature Importance (Random Forest Model) predicting trial participant's height

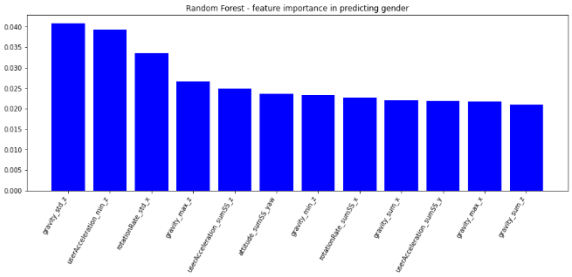


Figure 7 – Feature Importance (Random Forest Model) predicting trial participant's gender

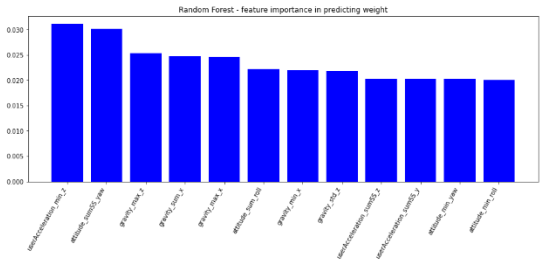


Figure 8 – Feature Importance (Random Forest Model) predicting trial participant's weight

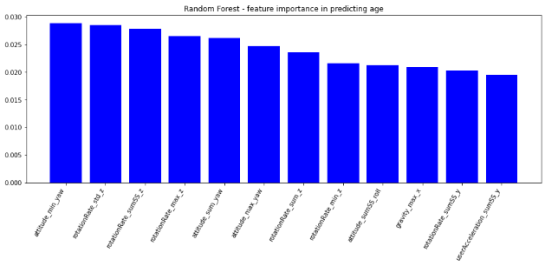


Figure 9 – Feature Importance (Random Forest Model) predicting trial participant's age

As the Random Tree classification model performed to the highest level of accuracy, a confusion matrix and feature importance graph is show below. The model had no errors predicting 3 trial participants - 5, 6 and 9. False positives are shown below the diagonal and false negatives are shown above.

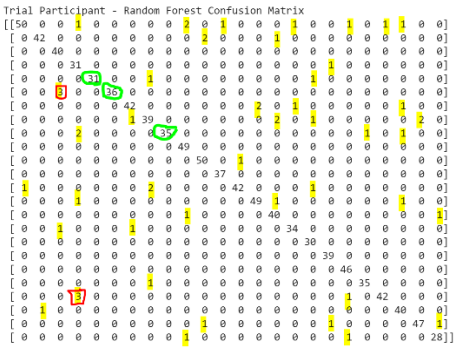


Figure 4 – Confusion Matrix (Random Forest Model) predicting trial participant

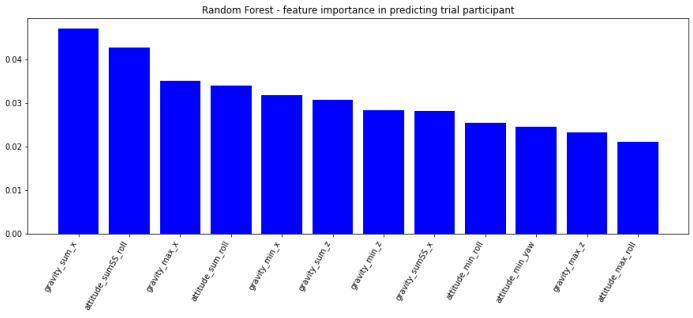


Figure 5 – Feature Importance (Random Forest Model) predicting trial participant

Random Tree confusion matrices for gender, weight and height had a higher number of false positives and age a higher number of false negatives. The false positives incorrectly predicted that gender was male or weight and height were above average. The false negative incorrectly predicted an age lower than the average.

References:

Y. Guan, 2019. *The role of feature Engineering on HAR* (GitHub) [ONLINE] Available at: https://github.com/yuguan1/CSC8111_code/blob/master/ML_day3/ML4HAR_1.ipynb [Accessed 14 January 2022].

A. Henriksen, M.H. Mikalsen, A.Z. Woldaregay, M. Muzny, G. Hartvigsen, L.A. Hopstock, S. Grimsgaard, 2018. *Using Fitness Trackers and Smartwatches to Measure Physical Activity in Research: Analysis of Consumer Wrist-Worn Wearables (Journal of Medical Internet Research)* [ONLINE] Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5887043/ [Accessed 16 December 2021].

Y.C. Huang, 2019. *My analysis on motion sensor data (Kaggle)* [ONLINE] Available at: https://www.kaggle.com/teaprint/my-analysis-on-motion-sensor-data [Accessed 16 December 2021].

D. Liftoff, 2019. *What Does Your Smartphone Know About You? (Kaggle)* [ONLINE] Available at: https://www.kaggle.com/morrisb/what-does-your-smartphone-know-about-you [Accessed 16 December 2021].

Kar, S.S. & Ramalingam, A., 2013. Is 30 the magic number? Issues in sample size estimation. *National Journal of Community Medicine,* 4(1), p. 175.

M. Malekzadeh, 2019. *MotionSense Dataset: Smartphone Sensor Data (Kaggle)* [ONLINE] Available at: https://www.kaggle.com/malekzadeh/motionsense-dataset [Accessed 16 December 2021].

S. O'Dea, 2021. *Number of mobile phones per household in the United Kingdom (UK) in 2020 (Statista.com)* [ONLINE] Available at: https://www.statista.com/statistics/387184/number-of-mobile-phones-per-household-in-the-uk/ [Accessed 16 December 2021].

J.L. Reyes-Ortiz, D. Anguita, A. Ghio, L.Oneto, X. Parra, 2012. *Human Activity Recognition Using Smartphones Data Set (UCI Machine Learning Repository)* [ONLINE] Available at: https://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones [Accessed 16 December 2021].

R. T, 2019. *A simple Features DNN using TensorFlow (Kaggle)* [ONLINE] Available at: https://www.kaggle.com/talmanr/a-simple-features-dnn-using-tensorflow [Accessed 12 January 2022].

S.T.A. Shaar, 2019. *Starter: MotionSense Dataset : 8c09b08d-5 (Kaggle*) [ONLINE] Available at: https://www.kaggle.com/salahuddinemr/starter-motionsense-dataset-8c09b08d-5 [Accessed 16 December 2021].

M. Shabaan, K. Arshad, M. Yaqub, F. Jinchao, M.S. Zia, G.R. Boja, M. Iftikhar, U. Ghani, L.S. Ambati, R.Munir, 2020*. Survey: smartphone-based assessment of cardiovascular diseases using ECG and PPG analysis (BMC Medical Informatics and Decision Making)* [ONLINE] Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7392662/ [Accessed 16 December 2021].

X. Sun, 2019. *Human Activity Recognition Using Smartphones Sensor Data (medium.com)* [ONLINE] Available at: https://medium.com/@xiaoshansun/human-activity-recognition-using-smartphones-sensor-data-fd1af142cc81 [Accessed 16 December 2021].

G.Wang, Q. Li, L. Wang, W. Wang, M. Wu, T. Liu, 2018. *Impact of Sliding Window Length in Indoor Human Motion Modes and Pose Pattern Recognition Based on Smartphone Sensors (Sensors – Basel, Switzerland)* [ONLINE] Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6021910/ [Accessed 16 December 2021].