Evaluating the Stressful Commutes Using Physiological Signals and Machine Learning Techniques

Mhd Saeed Sharif
School of Architecture, Computing and Engineering, UEL, London, UK
s.sharif@uel.ac.uk

Madhav Raj Theeng Tamang
School of Architecture, Computing and Engineering, UEL, London, UK
u1430774@uel.ac.uk

Cynthia H.Y. Fu
School of Psychology
Stratford Campus, London, UK
c.fu@uel.ac.uk

***Abstract*—Stress can be described as an alteration in our body that can cause strain emotionally, physically, or psychologically. It is a reaction from our body to something that demands attention or exertion. It can be caused by various reasons depending on the physical or mental activity of the body. Commuting on a regular basis also acts as a source of stress. This research aims to explore the physiological effects of the commute with an application of a machine-learning algorithm. The data used in this research is collected from 45 healthy participants who commute to work on a regular basis. A multimodal dataset containing medical data like biosignals (heart rate, blood pressure, and EEG signal) plus responses obtained from the questionnaire PANAS. Evaluation is based on the performance metrics that include confusion matrix, ROC/AUC, and classification accuracy of the model. In this research, several machine learning algorithms are applied to design a model which can predict the effect of a commute. The results obtained from this research suggest that whether the interval of commute was small or large, there was a significant rise in stress levels including the bio-signals (electroencephalogram, blood pressure and heart rate) after the commute. The results obtained from the employed machine learning algorithms predict that heart rate difference before and after commute will correlate with EEG signals in participants who have self-reported to be stress after the commute. The random forest algorithm gave a very promising result with an accuracy of 91%, while the KNN and the SVM showed the accuracy of 78% and 80% respectively.**

Keywords—stress assessment, commuting, EEG, heart rate, blood pressure, wearable device

I. Introduction

Commutes to work are an unavoidable source of stress for many, as they can pose a risk to their physical and mental health and stress can also decrease the performance at work [1]. The ability to regulate one's stress is an essential part of life and being aware of one's level of stress is crucial for making informed decisions on how to alleviate stress such as allocating time to wind down. Stress can result through mental, physical, or emotional responses to unfavourable events that happen in our surroundings. Stress can result in a number of serious illnesses and cumulative stress can induce anxiety, cognitive impairments, irritability, fatigue, depression, social isolation, low self-esteem, immunological diseases, and many other health conditions [2]. Stress is also linked to cardiovascular disease due to lower heart rate complexity [3].

Electroencephalogram (EEG) helps in monitoring and measuring the various electrical processes in the human brain [4]. EEG signals are the representation of the electrical activities in the brain. These signals can be recorded and employed to detect various mental diseases such as stress. EEG signals are collected using non-invasive devices which use sensor probes placed on the scalp. These devices record the digital samples of the electrical activity detected on the surface of the head. However, due to being unintrusive and detecting signals from such a distance from the brain a lot of noise and interference can be recorded as well. Therefore, it is necessary to clean data rigorously employing filters to remove noise and increase signals to noise ratio.

Heart rate is a crucial indicator when looking at levels of stress. The normal adult heart rate values lie between 60 and 90 beats per minute [5]. Many recent studies show that heart rate is one of the factors to identify the stress. Stress can affect on several fundamental control mechanisms of stroke volumes such as diastolic function and systolic function, which can raise our heart rate and increase our BP [6]. Recent studies have developed various technologies to recognize stress levels. The stress level can be determined by several variables, including BP, heart rate (HR), pupil diameter, heart rate variability (HRV), and cortisol [7].

This research is focused on the investigation of identifying stressful commutes using the correlation between the difference in heart rate pre-commute and post-commute and EEG readings in subjects that have experienced stressful commutes. The data entries are paired in accordance with our hypothesis and a form of control that only considered EEG data and stress labels to show the viability of accounting for EEG Beta low and heart rate correlation. The hypothesis was used to determine the effect of commuting on HR and EEG beta low signal correlation to predict stressful commutes.

Participant stress was determined by comparing the participant's positive PANAS score before and after the commute. If the participant's positive score had dropped after their commute, then an assumption was made that something during their commute had induced stress and resulted in a decreased positive PANAS score.

This allowed for the hypothesis to be structured as follows "It is expected that heart rate difference will correlate with EEG signals in participants who have self-reported to be stressed".

II. Literature Review

Stress is a common physiological response experienced by people frequently in our daily life due to their surroundings [8]. Stress will rise when people feel challenged or threatened. It makes people feel difficult to adapt to and balance both the internal and external environment [8]. EEG technology has been designed to monitor the stress level of people using brain signals [4]. The autonomic nervous system (ANS), which is made up of the antagonistically controlled sympathetic nervous system (SNS) and parasympathetic nervous system (PNS), is also known to be stimulated abnormally by stress[9]. Numerous cutting-edge wearable technologies such as Olive, Breath Acoustics, and Spire have been developed to measure the stress level in our daily lives. [8].

An offline LabView-based model was designed to analyse the EEG signals to monitor the stress level [4]. That model used a 1-channel EEG headset to record EEG and an mobile application was used to capture the recorded EEG signals. Their result shows that the Beta band of EEG will be higher than the Alpha band when people are stressed. Similar research was undertaken by Jaun and Ioannis where affect, mood, personality, and social context (individual vs group setting) were predicted using EEG signals and PANAS form [9]. This was achieved employing a SVM approach where fractal dimension features were extracted per EEG band as well as differential entropy per EEG band. Their literature indicated that these features were related to participant's emotional responses. They approached two scenarios that formed their dataset labels. Their results produced an accuracy of 68% using SVM with radial basis function with their arousal scenario and an accuracy of 61% using SVM with linear kernel function applied to their emotional valence scenario.

Convolutional Neural Networks are one of the popular deep neural networks showing promising result in image classification in the recent decade [10]. The human visual cortex, whose layers of neurons form maps of features that later layers use to build ever more complex features, is the biological model for CNNs. It uses convolutional filters, also referred to as kernels, to create feature maps, these feature maps are created by moving a grid over the matrix (Generally from top left to bottom right, horizontally layer by layer) and performing a chosen filter. These feature maps are then subsampled using a grid in the same manner but this time using a pooling rule, for example, max pooling. Max pooling examines all individual values within the grid and takes the highest value to create a down-sampled feature map. The process of using a kernel to produce a feature map can be expressed as the sum of the element-wise product of two matrices, the target image, and the kernel respectively [11].

Recurrent Neural Networks (RNN) are neural networks that contain recurrent units and are used to learn temporal features relating to sequence and order. Sepp Hochreiter and Jürgen Schmidhuber created Long-Short-Term Memory units in 1997 in an effort to address the vanishing gradient problem. These units are used in modern RNNs [12]. Each LSTM unit feeds into the next as a directed graph while also feeding into itself allowing it to remember the order of inputs that have gone through it. LSTM networks have shown good results in tasks where the order is a key component such as handwriting recognition and speech recognition.

Features are attributes that classes of objects share and can potentially be grouped by. Machine learning classification techniques aim to group objects by common features employing pattern recognition. One of the well-known machine learning methods that can perform well in a range of applications is the support vector machine (SVM) [13]. SVM is like linearly separable machine learning techniques such as linear regression but instead, they use a non-linear hyperplane to do so. Which an SVM is training the hyperplane is fit to separate the data in N dimensions where N are the features. Relatively they perform very well on classification problems that are low on training samples.

Wavelet transforms using different wavelets and their wavelet coefficient outputs have shown to be an effective means for EEG signal classification [14], [15]. Wavelets are used to define a signal through scaling and shifting to represent an approximation of a signal, like how the Discrete Fourier Transform can be used to approximate a signal using sinusoidal waves.

K-fold cross-validation is common validation method that involves randomly permuting the dataset label pairings and dividing the resulting permutation into K many groups. The K many groups will be divided into training and testing portions, with the possibility of excluding N many K groups to further reduce bias. This is performed for all K groups where a model is fit in accordance with the random permutations of train and test data. The K groups and models should be kept completely isolated so there is no data leakage. This results in K many models being trained, and the accuracy is given as the mean accuracy of all the models, additionally, statistics such as mean confusion matrices or confusion matrices that include all the correct/false positives and negatives can be generated from multiple models. If performed with a K large enough can make a machine learning model almost deterministic as the result will converge towards the true accuracy given a dataset.

EEG Beta Low power signals were broken down into their intrinsic mode functions using empirical mode decomposition. A function that satisfies the following requirements is said to have an intrinsic mode function. First, the dataset's extrema and zero-crossings must either be equal or have value differences of no more than one. Second, the envelope's mean value, which is determined by the local maxima and minima, must remain zero. Since empirical mode decomposition is symmetric with respect to 0 as specified in the second requirement, it is most frequently employed for Hilbert spectrum analysis[16].

Hilbert-Huang Transform uses the EMD to decompose a signal into intrinsic mode functions. Doing so allows for each intrinsic mode function to be analysed and produces an instantaneous frequency spectrum of the intrinsic mode functions [16]. Hilbert-Huang Transform has been used previously to pre-process EEG signals in order to improve the signal to noise ratio and enable meaningful features to be retrieved by machine learning methods such as CNN. EEG signals are non-stationary and are a good example to use HHT to extract time-frequency features.

Similarly, research was conducted to study how the OM mantra affects the brain, aimed to observe delta waves within 23 mediating test subjects using SVM, which classifies the presence of delta band brain waves by using statistical features from the recorded EEG signals. [17]. To investigate task-specific filters for categorization, an automatic sleep stage scoring system with single-channel EEG and convolutional neural networks was developed [18]. They achieved a mean F1 score of 81%, an individual sleep score of 82% and an overall accuracy of 74%. The results were gathered by using 20-fold cross-validation. The sleep stages which they classified included N1, N2 and N3 non-REM sleep, REM sleep and wake.

Hybrid deep neural networks are used in a research paper to classify brain EEG signals to recognize human emotional states. A hybrid network is composed of convolutional and recurrent neural networks [18]. The EEG signals were classified into four separate classes, high/low arousal, and high/low valence. Using this architecture, they were able to achieve 75.21 accuracies.

The non-invasive brain-computer interface was designed by a group of researchers to detect and classify human mental states using EEG signals [20]. In that research paper, EEG signals were used to classify the pilot's mental states while flying during continuous decoding. Seven pilots' EEG data were gathered in a variety of simulated flight scenarios.

A new kind of EEG classification network was proposed in a study to increase classification accuracy by end-to-end learning of the time and spatial aspects of EEG data[21]. The techniques presented describe an architecture that achieved an accuracy of 77.9% motor imagery, 89.91% and 88.31% for emotion classification. Similarly, an EEG classification method was proposed for classifying brain action states with a focus on advancing brain-computer interfaces and prosthetic control which employs the feature priority analysis and CNN [14]. In this method, EEG signals were classified using an already trained CNN known as AlexNet.

An EEG signal-based emotion recognition model was designed using the empirical mode decomposition method (EMD) to classify human emotion states using different machine learning techniques, [8]. SVM, linear discriminant analysis and Naive Bayes classifier were applied to those EEG data. EMD was used to separate the EEG signals into approximations of the intrinsic mode functions that make up the original signal.

III. IMPLEMENTATION

This study employs various machine learning techniques which are applied to design a model which can predict the stress level of humans after commuting using EEG signals. Receiver-operator characteristic (ROC) curve or AUC statistics and Confusion matrix were implemented to calculate the performance of the designed model. For each of the techniques, the data was first pre-processed dividing into training and testing data for each of the algorithm to validate the hypotheses. For the measured EEG Beta Low signal data there was only one band recorded which was while the participants were commuting to work. This posed a limitation where there was no discrete measurement of the participant's EEG before the commute. From this, it was a reasonable assumption to presume that the first 10% of the EEG Beta Low signal data was pre-commute as the participant was still in the mindset of pre commute and as such the first 10% of the EEG signal data was used as Pre commute while the latter 90% was used for post commute. EEG recording was started once they are ready to start the commute. Heart rate and PANAS data were collected before starting the EEG recording.

Two label sets were created, the hypothesis label set and the stress label set. The hypothesis label set sets out to try and show the correlation between EEG beta low brain waves and heart rate in participants who are stressed and grouping participants by the hypothesis condition will allow for the hypothesis to be tested. The stress label was used as a control to be able to compare the difference between the hypothesis labelling and classification based solely on stress. A participant was considered stressed if their positive PANAS score had decreased over the course of their commute.

A. Feed Forward Neural Network

Feed-forward neural networks also known as multi-layer perceptron are a very fundamental machine learning technique and are the basis of deep learning. ANNs are function approximators and can be used to fit a function to map a specific input to a specific output. ANNs are based loosely on biological neurons that pass on signals at different rates per node and can adaptively change how much signal gets passed on. The ANN architecture used was very simple using 9 input neurons (the same number as the number of features) with a single latent layer containing 10 neurons. The same data and label sets were used as with the SVM. The training, testing and validation split was 70%, 15%, and 15% and achieved the accuracy as shown in Fig. 1 and Fig. 2. We have used the train, test, and validation matrices. Test dataset is used to provide an unbiased evaluation of a final model fit on the training dataset.

Figure 1. A confusion matrix to depict the results of the SVM trained using EMD values and hypothesis labels.

Figure 2. Confusion matrix to depict the results of the SVM trained using EMD values and stress labels.

B. Support Vector Machine

To train the Support Vector Machine, nine statistical features were chosen from the dataset, seven of these features were extracted from the EEG Beta Low signals. The seven statistical features as band power, interquartile range, kurtosis, mean, median, standard deviation and variance were chosen from the EEG Beta Low signals.

In this research, heart rate, blood pressure and EEG signals are collected from participants during their commute to work. Heart rate and blood pressure are two very relevant features in relation to human stress as they are correlated with stress levels [23]. The dataset contains before and after reading for HR and BP.

Using the pre-commute and post-commute HR, a heart rate difference value was calculated for each participant describing the increase or decrease of the participant's heart rate after the participant’s journey.

Similarly, systolic and diastolic blood pressure were recorded before and after the commute. Systolic blood pressure refers to the amount of pressure in the circulatory system when the heart muscles are pumping blood through it. Diastolic blood pressure refers to the amount of pressure in the system after one cardiac cycle, and measures the pressure in the system when the heart is in the brief period of rest in between cardiac cycles.

All the statistical features extracted were normalized with respect to the values of their respective categorical set. Normalization of the feature variables allows for each statistical feature to hold equal weight when being used within machine learning models. Without normalization, situations are likely to occur where a feature has a much larger numerical value than another such as EEG brain signal values which are normally measured in microvolts and could be in the thousand and heart rate difference pre-commute and post-commute will be single or low double digits.

Firstly, a label set was created using the hypothesis as a condition where if beta low after commute was greater than beta low before commute and the participant was stressed, they were labelled as positive in accordance with the hypothesis. If the participant's beta low was lower after commute compared to beta low before commute and the participant was not stressed, they were also labelled as positive in accordance with the hypothesis as both variables are correlating with the self-reported PANAS stress variable. As stated previously stress labels were created using the PANAS self-report, if the participant’s positive score had decreased after the commute, then it was assumed that they had a stressful commute in some way.

The outputs of the SVM were validated using K-fold cross-validation, which was carried out at K of 10 to account for any potential bias or fluctuation. The SVM consistently gave the same accuracies at K of 10. The Radial Basis Function was the training function that was utilised to fit the SVM. 70% of the data were from the train, and 30% from the test.

C. Predicting stressed state using PANAS stress labels

As a form of control for the experiment, all the previous models were also trained using a dataset that contained the same data but was differently labelled. This dataset used the same EEG beta low band data but was labelled positive and negative in accordance with a stressful commute based solely on the participant’s pre and post PANAS scores. Doing so allows for the observation of the effect of labelling data in accordance with EEG beta low and heart rate correlation and provides a base comparison where the base case does not consider heart rate. Fig. 3 and Fig. 4 show the SVM trained on power values with the two label sets. Here the hypothesis accuracy is considerably lower than the stress label accuracy.

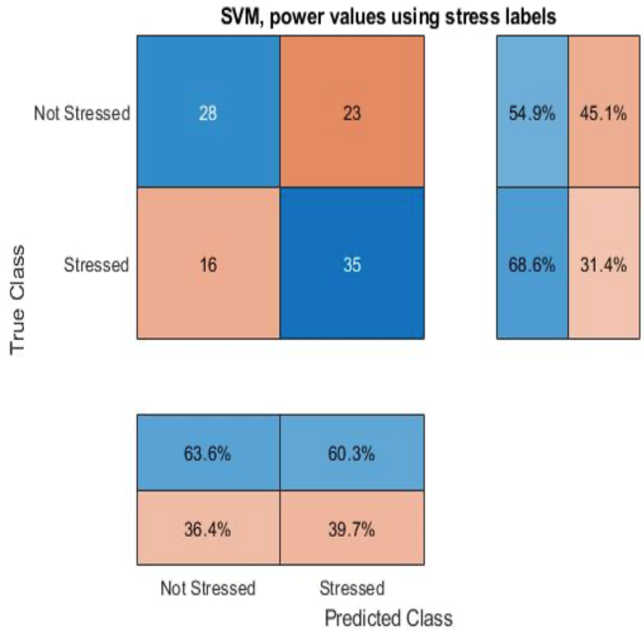

Figure 3. Confusion matrix to depict the results of the SVM trained using raw power values and stress labels.

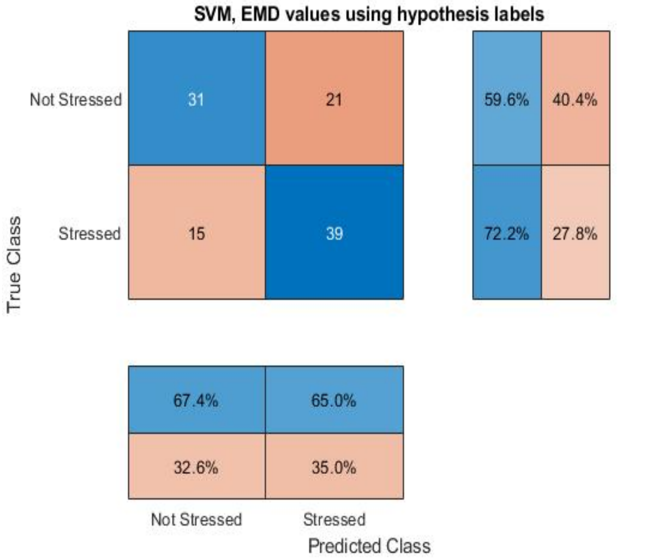

Figure 4.A confusion matrix to depict the results of the SVM trained using raw power values and hypothesis labels.

D. K-Nearest Neighbor

A K-nearest neighbour classifier was trained using the four datasets and 2 labels resulting in 8 models being trained. The same datasets and label sets were used to train the KNN classifier. KNN classifiers use a K number of neighbours to classify classes. A K number is given where k is the number of the closest nodes to look at and then decide what class the node belongs to by the largest number of closest nodes of a specific type. Distance between nodes is usually the Euclidian distance. For this classifier, the K number chosen was 5. The KNN performed well with an accuracy of 83.75% and 79.7% for hypothesis and stress label respectively.

IV. Results and discussion

The accuracy for each model was calculated using:

$$Accuracy = ((TP+TN) / (TP+FN+FP+TN)) \times 100\% \quad (1)$$

This method for calculating accuracy is a much more robust method of quantifying model performance as it considers all possible outcomes of a binary classifier as opposed to the more general true positives divided by total samples as shown in equation (1).

The SVM trained with the lowest accuracies out of the 3 models and trained with the lowest accuracy of 61.85% using stress labels and 66.2% for hypothesis labels. The ANN trained very well overall, producing good accuracy for both stress and hypothesis labels with the hypothesis labels scoring 87.50% The KNN performed well on average for all datasets and labels with an accuracy of 83.75% for hypothesis labels and 79.7% for stress label.

Overall, the ANN trained with the highest accuracy for both stress and hypothesis labelled data with the hypothesis labels reaching 87.5% as shown in the Table I below.

Table I. Machine learning techniques with accuracy for hypothesis and stress label.

Model	Validation Accuracy
SVM, EMD IMF 1, Hypothesis label	66.20%
SVM, EMD IMF 1, Stress label	61.85%
ANN, EMD IMF 1, Hypothesis label	87.50%
ANN, EMD IMF 1, Stress label	80.04%
KNN, EMD IMF 1, Hypothesis label	83.75%
KNN, EMD IMF 1, Stress label	79.7%

V. Conclusion

In this study, we used a variety of machine-learning techniques to create a smart model that can estimate how the commute will affect our bio signals. For classification models to be able to classify data there needs to be enough distinction and correlation. The hypothesized labels indicated participants who were expected to be stressed and the self-reported stress labels are indications of people who say they are stressed. The results are mixed showing some high results for both hypothesis labels and stress labels. The hypothesis labels had higher accuracies than the three models.

The hypothesis labels performed with the highest accuracy using an ANN performing at 87.5%. As the highest accuracy attained for each model was with the hypothesis labels this is supportive of the hypothesis that Beta Low brain waves correlate with heart rate in individuals who are stressed.

Similarly, the outcome of the machine-learning approaches also supported our hypothesis, which held that if individuals reported a stressful commute, the heart rate difference between commuting will be correlated with EEG Beta Low power. We have used PANAS questionnaire as a subjective self-report quantitative measure. The result obtained from the PANAS suggested that there was rise in negative effect after the commute. Similarly, the positives of participants after commute were less positive after the commute to work.

For future work, more variables could be considered when classifying stressful commutes or experimenting with identifying the general mood of participants using sequence to sequence to predict a participant's sequence of PANAS values from the input of EEG brain signal data.

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