Innovative Computation to Detect Stress in Working People Based on Mode of Commute

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ABSTRACT

Introduction:

Commuting is an integral part of modern life for many people, shaping daily routines and impacting overall well-being. With various transportation options, including driving, public transport, walking, and cycling, commuters encounter various experiences and challenges in their everyday journeys. Understanding how different modes of commuting affect stress levels is essential for improving public health and informing transportation planning. This study develops advanced machine-learning techniques to explore the connection between commuting methods and stress levels.

Methods:

This research examines how different commuting modes affect stress levels using machine learning methods. The study analyses data collected from 45 individuals who regularly commute to work, focusing on driving, walking, cycling, and public transport modes. Non-invasive wearable sensors were utilised to gather electroencephalography (EEG), blood pressure (BP), and heart rate (HR) data for five consecutive days for each participant. Additionally, qualitative data was collected using the Positive and Negative Affect Schedule (PANAS) questionnaire to assess participants' emotional responses before and after their commute. The research focuses on developing a machine learning-based model to predict the commute's impact and monitor the stress level due to the commute mode. In research, objective and subjective factors shape the research process and outcomes. Understanding the interaction between these factors is essential for conducting thorough and reliable research that produces valid results. Our study utilises datasets incorporating qualitative and quantitative data from questionnaires and human bio-signals.

Results:

Similarly, this research developed various machine learning algorithms to detect stress levels based on commuting mode. The results indicate that the Linear Discriminant Analysis technique achieved an accuracy of 88%, while Logistic Regression reached 90.66% accuracy. The Boosted Tree algorithm produced the best performance, with an accuracy of 91.11%. Furthermore, incorporating personalized parameters into the data improved the accuracy of these algorithms in detecting stress levels. Cross-validation was also utilized to mitigate the risk of overfitting, ensuring robust and reliable model performance.

Conclusions:

The findings reveal that human bio-signals tend to increase following commuting, irrespective of the mode, with driving identified as the most stressful option. Commuters using passive modes of transport experience elevated stress levels compared to those using active modes. This research underscores the importance of understanding the connection between commuting modes and stress, providing key insights into the potential health impacts of daily travel. The development of an intelligent model to predict stress levels based on commuting mode offers valuable contributions to public health and transportation planning, with the goal of enhancing well-being and improving commuters' quality of life.

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1. Introduction

The commute has become an integral part of our everyday lives. Most of the world's major cities grapple with transportation and traffic issues, attributed to the rapid growth in human population and vehicles on the road. Technology can potentially aid in developing and managing sustainable commuting modes (Iyer, 2021). Commuting can often be regarded as one of the least enjoyable among various daily activities (Kahneman, Krueger, Schkade, Schwarz and Stone, 2004).

Commuting is an integral aspect of daily life for working individuals, while children's school-related travel remains unavoidable despite its adverse health effects. The correlation between the health impact and commuting distance is directly proportional: longer journeys yield more severe health consequences, while shorter commutes have a lesser effect. The government is actively advocating for active transportation modes to support public health initiatives. The UK government has implemented a scheme encouraging individuals to opt for walking and cycling over cars, aiming to shift towards more active modes of travel (Abou-Zeid, Witter, Bierlaire, Kaufmann and Ben-Akiva, 2012). This initiative seeks to improve public health and decrease car emissions. Cross-sectional data provides additional evidence supporting the health benefits associated with active transportation. The UK's National Institute for Health and Care Excellence endorses active commuting through walking or cycling as a government-backed public health measure.

Commuting exerts a crucial impact on physical and mental health, notably manifesting in stress, a critical concern associated with various forms of travel. The morning rush to work or school often fosters an unpleasant commuting experience, contributing to stress across nearly all commuting types. However, specific modes of transportation may exacerbate stress more than others. Pinpointing the specific stress-inducing factors within diverse commuting modes offers insights for policy interventions promoting sustainable transportation and effectively reducing stress levels. Stress, encompassing physical, emotional, and mental pressures, emerges in response to stimuli demanding attention or action. Daily life presents several stressors, including work, finances, relationships, parenthood, and everyday hassles, contributing notably to stress. While stress is unavoidable, preventive measures are pivotal in managing it (Bakker, Holenderski, Kocielnik, Pechenizkiy and Sidorova, 2012). Expert assessment remains crucial in evaluating an individual's stress levels within their current context. Traditional questionnaires are commonly employed to subjectively assess and quantify stress levels, symptoms, and related factors (Jun and Smitha, 2016). Automated stress identification and detection using physiological signals can mitigate health risks and contribute to societal well-being (Deng, Wu, Chu, Zhang and Hsu, 2013). Developing an intelligent system leveraging physiological data for automatic stress detection is imperative to meet this need. Such a system should analyse physiological signals accurately, identifying stress presence and intensity without relying on manual assessment methods. The project's overarching goal is to predict travel's health impact using machine learning algorithms, enabling people to plan alternative or active travel modes to prevent health risks such as blood pressure and heart disease, ultimately safeguarding public health. Various AI techniques, including Linear Discriminant, Boosted Trees, and Logistic Regression algorithms, are employed to predict the health impact on participants commuting through different modes.

The study focuses on the impact of commuting on physical and mental health, an issue of growing concern in urban areas worldwide due to increasing traffic congestion and associated stress levels. By leveraging machine learning techniques, the research aims to predict the health impact of commuting and promote alternative or active travel modes to mitigate health risks such as blood pressure and heart disease. This approach aligns with public health initiatives advocating for sustainable transportation options. The research integrates various data sources, including physiological signals, commuting patterns, and subjective assessments of stress levels, to understand the health impact of commuting. This approach enhances the depth and accuracy of the analysis. The study seeks to develop intelligent systems capable of automatically detecting stress using physiological signals, such as heart rate, blood pressure and EEG data. This study explores the social and neurophysiological effects of real-time commuting by leveraging machine learning to analyse brain waves and bio-signals. Commuting has become an essential and unavoidable part of daily life in modern society. Through this research, we aim to develop a novel model that uses bio-signals and an intelligent analytical approach to examine the health impacts of commuting.

2. Related Literature Review

Stress has ingrained itself into our daily lives, affecting most people at various points. However, persistent or heightened stress levels can disrupt our well-being and usual activities. Recent studies in transportation have focused heavily on the commuter's personal experience. Our understanding of travel behaviour, particularly in the choice of transportation mode, now relies more on factors like an individual's satisfaction with their journey, overall life contentment, and the stress experienced during commuting (Abou-Zeid et al., 2012). Previous research indicates that severe traffic congestion stands as the primary contributor to air pollution in mega-cities, consequently elevating morbidity rates in metropolitan areas (Olayode, Tartibu and Okwu, 2021).

A study utilised diverse machine learning techniques to identify stress through multi-modal data acquired from wearable sensors (Bobade and Vani, 2020). This research emphasises the urgency of early detection of mental stress to prevent various health complications linked to stress. Employing k-nearest neighbour, Linear Discriminant, Random Forest, Decision Tree, AdaBoost, and Kernel Support Vector Machine, the study achieved varying accuracies: 81.65%, 93.20%, 84.32%, and 95.21%, respectively.

A recent study aimed to employ machine learning techniques in the transportation sector to foster a sustainable society (Iyer, 2021). As the population grows, several cities grapple with numerous transport, traffic, and logistics-related challenges. AI technologies can be implemented in transportation to alleviate congestion, enhance the reliability of commuting experiences, and reduce stress. With escalating environmental concerns, AI has emerged as a solution to combat climate change and various other issues by modernising established industries and systems. It has facilitated the creation of environmentally friendly cities by aiding governments in preserving biodiversity and promoting human well-being.

A study indicated that individuals using active modes of transportation, such as walking, cycling, or public transit, experienced greater psychological well-being and happiness than those who drove. Moreover, transitioning from driving to active modes of transport contributed to an increase in overall well-being. Interestingly, a longer journey duration benefited pedestrians, whereas the opposite was true for drivers. Driving, as revealed, demands continual focus and may lead to feelings of boredom, social isolation, and tension (Martin, Goryakin and Suhrcke, 2014).

Another study conducted in Canada suggested a positive association between using active modes of commuting (walking/cycling) and improved well-being in contrast to passive commuting methods (Herman and Larouche, 2021). Active commuters exhibited a 35% lower likelihood of reporting dissatisfaction than passive commuters. Additionally, commuters who drove reported higher stress levels than those using active transport modes. Interestingly, regardless of whether the commute was active or passive, individuals using active modes reported greater post-commute satisfaction. However, commuter satisfaction decreased with longer commute duration (Chatterjee, Chng, Clark, Davis, De Vos, Ettema, Handy, Martin and Reardon, 2020). Similarly, transitioning from passive to active commute modes was associated with increased well-being (Knott, Panter, Foley and Ogilvie, 2018).

Numerous studies have been conducted to investigate the detection of stress levels in humans, employing diverse approaches. Ghaderi et al. researched stress by studying various bio-signals such as heart rate, respiration levels, and galvanic skin responses from both the foot and hand (Ghaderi, Frounchi and Farnam, 2015). Conversely, another study focused solely on using Electrocardiogram (ECG) data to gauge stress levels (Liu and Ulrich, 2014). In this research, the team developed a stress level prediction model centred around ECG data. Additionally, an author conducted experiments to detect stress levels using various physiological parameters (Shanmugasundaram, Yazhini, Hemapratha and Nithya, 2019). This study suggested crucial human bio-signals, including blood pressure, heart rate, temperature, vocal tone, and humidity, played pivotal roles in stress detection.

The study explored uncomfortable and stressful scenarios encountered while driving, employing a portable sensor system for data collection (Niermann and Lüdtke, 2021). This system captured various bio-signals, including heart rate, skin conductance, sitting position, and g-forces. The study aimed to establish correlations between self-reported subjective stress levels and the obtained sensor values by collecting these data points. The gathered data offered valuable insights into the physiological responses associated with stress during driving. Specifically, increased heart rate, elevated skin conductance levels, alterations in sitting position, and high g-forces were identified as potential indicators of stressful situations. A neural network model was employed to analyse and predict stress levels based on the collected data. This model predicted the stress that people would experience while driving by using the relationships found between biosignals and self-reported stress levels.

Utilising this sensor system and neural network model, the research aimed to provide a quantitative and objective assessment of stress levels during driving. This approach sought to deepen our comprehension of stress-contributing factors in driving scenarios, potentially leading to developing interventions or strategies to mitigate stress and enhance safety and comfort during driving experiences. The study referenced conducted an analysis using physiological data to gauge the stress levels of drivers (Healey and Picard, 2005). This involved the continuous collection of Electrocardiogram (ECG), Electromyogram (EMG), skin conductance, and respiration data from drivers navigating open roads in greater Boston for a minimum of fifty minutes. The study aimed to uncover correlations between these physiological signals and observed stressors through two distinct analytical approaches. Results highlighted that, for most participating drivers, skin conductance and heart rate metrics exhibited the most robust correlations with their stress levels. This finding suggests that physiological signals could be reliable indicators for assessing driver stress, especially in forthcoming vehicles equipped with physiological monitoring capabilities. Such metrics could be instrumental in managing noncritical in-vehicle information systems, ensuring their timing and presentation are optimised to minimise driver stress. Additionally, this data could enable continuous assessment of how road and traffic conditions impact drivers, leading to a deeper understanding of stress-inducing factors in driving environments.

The research introduces a real-time, non-intrusive monitoring system to detect drivers' emotional states by analysing their facial expressions (Gao, Yüce and Thiran, 2014). Ensuring the driver's attentiveness and emotional state is crucial for driving safety and comfort. Specifically, the system aims to identify two primary negative emotions—anger and disgust—associated with stress. It detects individual emotions in each video frame and then assesses stress levels at the sequence level.

Experimental results illustrate that the developed system effectively performs, even with simulated data and generic models. Additionally, the system incorporates an extra step for pose normalisation to minimise the impact of camera setup and pose variations, thereby improving the accuracy of emotion detection. Overall, this research presents a robust and real-time monitoring system capable of accurately discerning the driver's emotional states through facial expression analysis. The system provides valuable insights into the driver's emotional well-being by addressing stress-related emotions and integrating pose normalisation techniques, enhancing driving safety and comfort.

Commuting to work has become an integral part of daily routines, and its various aspects, including travel mode, time, and distance, have been linked to predictors of stress and well-being. Studies have revealed correlations between commuting, higher blood pressure levels, and increased perceived stress (Gottholmseder, Nowotny, Pruckner and Theurl, 2009). In one research effort, data from working individuals was utilised to detect stress levels using different sensors (Nakashima, Kim, Flutura, Seiderer and André, 2015). These sensors collected diverse bio-signals such as heart rate, blood volume pulse, and eye movements. Similarly, an experiment measured stress levels by simulating events or tasks that induce stress, leading to physical or mental strain (Gedam and Paul, 2021). Observations during these stress-inducing events revealed notable rises in key bio-signals, including heart rate, blood pressure, and galvanic skin conductance. These physiological markers exhibited increases, indicating heightened physiological responses associated with the simulated stress-inducing situations.

A research study employed machine learning techniques to detect participants' stress levels, utilising data collected from smartwatches (Katarya and Maan, 2020). Parameters like HRV, blood pressure, skin temperature, and sleep patterns were harnessed to gauge and quantify stress levels. These diverse physiological indicators were amalgamated to assess stress levels effectively. The study applied multiple machine learning algorithms, including SVM and KNN, to the data, aiming to detect stress levels and compare the accuracy of the different techniques. Numerous studies have suggested that combining various bio-signals can enhance accuracy within machine learning algorithms compared to models using a single bio-signals (Sriramprakash, Prasanna and Murthy, 2017; Siirtola, 2019; Muaremi, Bexheti, Gravenhorst, Arnrich and Tröster, 2014).

In summary, research on stress and commuting, machine learning applications in transportation, detecting stress levels through physiological signals, facial expression analysis for emotional state detection, and using bio-signals have shown substantial advancements. These studies link commuting factors with stress predictors, utilise physiological data for stress detection, and explore machine learning using multiple bio-signals, highlighting the potential for enhanced accuracy.

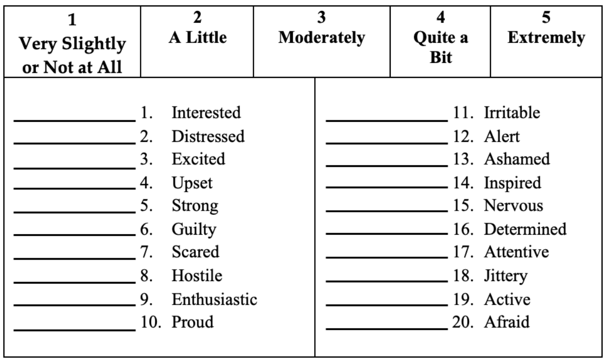
3. Research Methodology

The research focuses on developing a machine learning-based model to predict the commute's impact and monitor the stress level due to the commute mode. In research, objective and subjective factors shape the research process and outcomes. Understanding the interaction between these factors is essential for conducting thorough and reliable research that produces valid results. Our study utilises a dataset incorporating qualitative and quantitative data from questionnaires and human bio-signals. Thus, several steps are carried out to determine the stress level, as explained below:

3.1. Data Collection

In this research, 45 healthy participants were recruited with a mean age of 32 years, which consists of 18 females and 27 males. Using the simple random sampling method, the sample size required for our study was found to be 42 only.

However, several similar studies have been conducted with smaller participant numbers than our research. For instance, one study focused on detecting stress levels through machine learning and deep learning with multimodal physiological data from only 15 subjects (Attar, Balasubramanian, Subasi and Kaya, 2021). Another successful study utilized machine-learning-based signal processing on physiological signals for stress detection with data from just 17 drivers (Ghaderi et al., 2015). The study participants in our research were working people and had regular commute routines to work. They resided in various locations across London. For five consecutive days, non-invasive wearable technologies were employed to gather the participants' bio-signals, including heart rate, BP, and electroencephalography signals. These wearable devices allow the collection of physiological data in a non-disruptive manner throughout the study duration. The EEG signal was recorded using the EEG headset, allowing for the continuous monitoring of brain activity throughout the commuting experience. This device captured and recorded the brain's electrical activity, providing valuable EEG data for analysis and examination in the study (Sulaiman, Ying, Mustafa and Jadin, 2018). For each participant, we collected blood pressure and heart rate measurements before and after their commute over five consecutive days, yielding a total of 450 data points for each measure. Additionally, EEG data was recorded throughout the commute using the Neurosky headset, which sampled brain signals at 512Hz, which means the device records 512 datapoints per second. The average commute duration was 35 minutes. A questionnaire form called the Positive and Negative Affect Schedule (PANAS) was employed as part of the study, as shown in Figure 1. This questionnaire served as a measure to assess participants' subjective experiences of positive and negative affect, allowing them to report their emotional states and feelings. The PANAS questionnaire provided valuable subjective data that complemented the objective physiological measurements collected in the study. The utilisation of this questionnaire as a self-reported measure of affect has gained broad acceptance in both community and clinical contexts (Watson, Clark and Tellegen, 1988; Clark, Tellegen et al., 1988). The PANAS has 10 positive and 10 negative items to ensure a balanced, comprehensive, and empirically validated measure of both types of affects, reflecting the complexity of human emotional experience. Survey results further indicated that active modes of commuting correlated with increased physical activity, lower BMI, and reduced risk of obesity (Flint, Cummins and Sacker, 2014; Larouche, Faulkner and Tremblay, 2016). Similarly, Heart rate and BP were obtained pre-commute and post-commute using the MySignal device. Additionally, EEG data was collected during the commute using the Neurosky EEG headset. Alpha and Beta bands were utilised from the EEG signal as presented in Figure 2.



1 Very Slightly or Not at All	2 A Little	3 Moderately	4 Quite a Bit	5 Extremely

________ 1. Interested	________ 11. Irritable
________ 2. Distressed	________ 12. Alert
________ 3. Excited	________ 13. Ashamed
________ 4. Upset	________ 14. Inspired
________ 5. Strong	________ 15. Nervous
________ 6. Guilty	________ 16. Determined
________ 7. Scared	________ 17. Attentive
________ 8. Hostile	________ 18. Jittery
________ 9. Enthusiastic	________ 19. Active
________ 10. Proud	________ 20. Afraid

Figure 1: Subjective self-report questionnaire.

The collected data was divided into two sub-datasets. The first dataset comprised the key parameters, including BP, HR, and EEG signals. In addition to these primary parameters, the second dataset incorporated personalised factors such as height, alcohol and smoking status, age, weight, and weather conditions. By combining these personalised parameters, the second dataset provided a more comprehensive and personalised perspective on the relationship between stress and commuting.

3.2. Feature Extraction

In this study, heart rate, BP, and EEG signals were recorded to predict the impact of commuting on individuals. By comparing the post-commute values of blood pressure and heart rate with their respective pre-commute values, it was possible to determine if the participants experienced an increase, which indicates a state of stress. This analysis

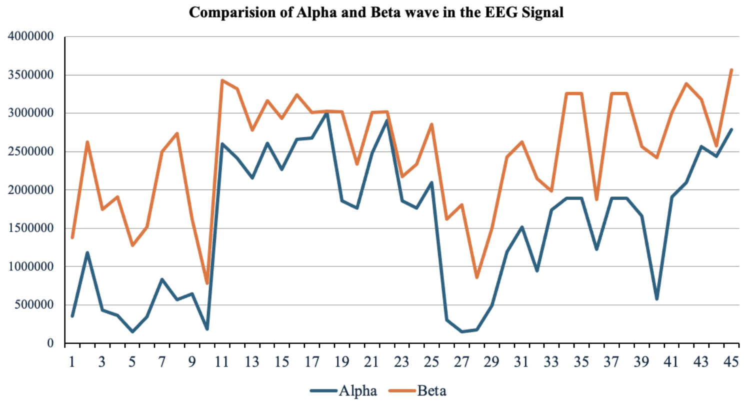


Figure 2: Comparison of Alpha and beta wave from the EEG signal after the commute.

provided insights into the physiological response to commuting and its potential impact on stress levels. Similarly, when the centroid value of the Beta band is higher than the Alpha value, it denotes that the participants are stressed (Sulaiman et al., 2018).To apply various machine learning algorithms, pre-processed data was used for each method to evaluate the following research hypothesis: After commuting, if EEG beta low power is greater than alpha low power, the individual is stressed. This hypothesis was tested to detect stress levels following the commute. EEG and blood pressure data were collected from participants during their commute. The EEG data consists of five distinct frequency bands: delta, theta, alpha, and beta. For this study, only the alpha and beta bands were analysed, as the alpha band is associated with relaxation, while the beta band is linked to active thinking, alertness, or stress. Additionally, systolic blood pressure was selected from the recorded BP measurements, as it represents the pressure when the heart contracts to pump blood and is considered a stronger indicator of stress compared to diastolic pressure. Also, the PANAS result can help determine whether the participant is stressed or not (Merz, Malcarne, Roesch, Ko, Emerson, Roma and Sadler, 2013). It is categorised into low and high stress to identify their stress level. The threshold value for each parameter is calculated. A combination of baseline and stress-condition data was collected to determine the threshold for identifying stress using bio-signals like blood pressure, heart rate, and EEG. First, baseline measurements were recorded when individuals were relaxed and non-stressed to establish normal ranges for each signal. Then, data was gathered under stress-inducing conditions to identify physiological changes. Statistical methods, such as mean and standard deviation differences between baseline and stress conditions, were used to establish thresholds. For example, elevated systolic blood pressure, an increased heart rate, and a shift in EEG activity (such as increased beta and decreased alpha power) were commonly associated with stress. These values were analysed using machine learning models to determine a threshold accurately distinguishing between stressed and non-stressed states. If the value of the bio-signal is higher than the threshold value, it is considered high stress.

After the data collection phase, the next step involved defining the dependent and independent variables, which are crucial for constructing the machine-learning model. The choice of these variables was based on the research question and objectives of the study. In this machine-learning model, the dependent variable, also referred to as the target variable, was derived from the main parameters associated with changes in blood pressure, heart rate, and EEG (electroencephalogram) signals. These parameters indicated physiological responses to various stimuli, including stress and relaxation. The participant collected bio-signals, specifically blood pressure and heart rate, both before and after the commute to work. Additionally, continuous monitoring of the EEG signal was performed throughout the commute. These bio-signals served as primary indicators of physiological changes in response to different commute modes. Following the data collection phase, the target variables were derived from the collected data, focusing on assessing the impact of commute mode on the observed bio-signals. This involved analysing how variables such as blood pressure, heart rate, and EEG patterns varied with different modes of commuting, such as driving, cycling, or public transportation. Conversely, the independent variables, also known as features or predictors, encompassed a broader range of parameters beyond the bio-signals. These included demographic factors such as age, gender, and height and lifestyle factors like age, height, medication intake, weight, and smoking and alcohol status as shown in Table 1. These additional parameters were incorporated into the model to account for potential confounding variables

Table 1
The demographic information of the study population.

Parameter	Mean	Standard Deviation
Duration of commute	35.16	9.95
Age (Years)	32.28	8.42
Weight (Kg)	66.64	10.79
Height (cm)	168.52	12.17
Cigarettes (Per day)	0.73	1.51
Alcohol intake (Weekly units)	1.42	3.05
Temperature (Degree Celsius)	18.25	4.26

and provide a more comprehensive understanding of the factors influencing physiological responses during commuting. By incorporating both dependent and independent variables into the machine-learning model, we aimed to develop a predictive framework capable of assessing the impact of commute mode on bio-signals. This approach allowed for a more nuanced analysis of the relationship between commuting behaviour and health outcomes, ultimately informing strategies for promoting healthier and more sustainable transportation practices.

4. Implementation

A model based on machine learning techniques has been developed to execute the data set. Different pattern algorithms have been chosen to improve the performance. The analysis used Boosted Trees, Linear Discriminant, and Logistic regression algorithms. The analysis was conducted to treat the data and get the output. The data will be processed from the output file, which is input and loaded into the system for the results. The flow chart for the whole process of this study is shown in Figure 3.

4.1. Metrics for evaluating classification performance

4.1.1. Confusion Matrix

The confusion matrix is the most commonly used evaluation metric for machine learning classification problems. It is a graphical representation of the classifier's generated predictions and the actual values. A confusion matrix is a tabular representation that comprehensively summarises a classification model's performance. It presents the counts of true positive, true negative, false positive, and false negative predictions made by the model. Examining the confusion matrix can gain valuable insights into the classifier's performance, including accuracy, precision, recall, and F1 score. These metrics aid in evaluating the model's ability to classify the data accurately.

4.1.2. Precision

Precision refers to the ratio of accurately predicted and expected positive instances. When the data set is unbalanced, meaning that one class is more prevalent than the others, relying solely on accurate categorisation can lead to misleading results. For example, a model can attain a high accuracy score by consistently predicting the most prevalent class for all outputs without acquiring substantial knowledge or insights from the data. To tackle this issue, precision is computed as a metric to identify the proportion of accurate positive predictions, as shown in Equation 1.

$$Precision = TP/TP + FP \tag{1}$$

4.1.3. Recall

The true positive rate (TPR), also called recall, quantifies the percentage of true positive instances that are accurately classified. It is determined using a specific Equation 2.

$$Recall = TP/TP + FN \tag{2}$$

In this equation, TP represents the number of true positives (correctly predicted positive instances), and FN represents the number of false negatives (positive instances incorrectly predicted as negative). It calculates the recall or true positive rate by dividing the number of true positives by the sum of true positives and false negatives. It is a

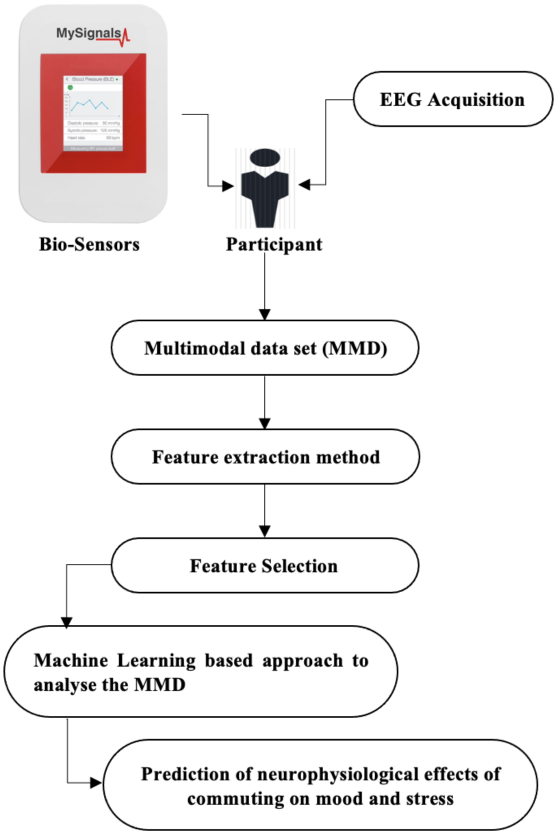


Figure 3: Flow chart of the whole project.

useful metric for assessing the model's ability to correctly identify positive instances, accounting for missed instances (false negatives).

4.1.4. The Area under ROC Curve

The performance of the algorithm can be evaluated by receiver-operator characteristic (ROC) (Hajian-Tilaki, 2013). ROC applies a threshold value for each output value. Each algorithm exhibits distinct true positive and false positive values. The data needs to undergo pre-processing, divided into different subsets. The dataset will be divided into three subsets: the training data, which will comprise 70% of the dataset; the validation data, which will represent 20%; and the remaining 10%, which will be allocated as the test data. The 70% training data allows the model to learn effectively, while the 20% validation set helps fine-tune the model and prevent over-fitting. The final 10% test set provides an unbiased assessment of the model's performance on unseen data, ensuring it generalises well to new inputs.

5. Results and Discussion

In our study, we split the data into two separate data sets. The first set includes the key parameters, BP, HR, and EEG signals. On the other hand, the second data set comprises the BP, HR, EEG signals and additional personalised parameters gathered from the subjects.

By splitting the data into these two categories, we can examine the impact of subjective parameters on the analysis separately from the objective parameters. This division allows us to compare and analyse the influence of subjective factors on the outcome variables while controlling for objective factors.

The objective parameters (blood pressure, heart rate and EEG signal) provide direct physiological measurements that can be considered more concrete and less prone to bias or individual interpretation. On the other hand, subjective

Table 2
Confusion matrix of Boosted Trees for the first dataset.

	Predicted Positive values	Predicted Negative values
True Positive Values	95 (True Positive)	13 (False Positive)
True Negative Values	14 (False Negative	103 (True Negative)

parameters (age, height, weight, and alcohol consumption) involve self-reported information that individual perceptions or reporting errors may influence. By analysing the two data sets separately, we can assess the relative importance of subjective parameters in explaining variations in the outcome variables compared to the objective parameters alone. This approach helps understand the complex relationship between different factors and their impact on the variables of interest.

5.1. Using only the main parameters of Heart rate, BP, and EEG signals

5.1.1. Boosted Tree

It refers to an ensemble learning method that combines multiple decision trees to create a predictive model. Boosted trees are built sequentially, where each subsequent tree is constructed to correct the mistakes made by the previous trees. Boosting addresses the errors made by preceding decision trees. Boosting transforms weak decision trees into strong learners. In boosting, subsequent trees are constructed by considering previous trees' mistakes. As a result, the trees are built sequentially, with each tree relying on the one that came before it. This approach is known as sequential learning, which is unsuitable for parallel computing. Once the model was trained, we achieved an accuracy 88% with five-fold cross validation. The Confusion matrix is utilised to evaluate the algorithm's accuracy, which provides a comprehensive overview of the algorithm's performance, showcasing the correct and incorrect predictions made for each class in a tabular format (Visa, Ramsay, Ralescu and Van Der Knaap, 2011). The model predicted 95 values were correct out of 108 for the first class. Similarly, the second class had 14 misclassified values out of 117. The overall performance of this algorithm is shown below in Table 2.

The ROC curve was created to demonstrate the overall performance of this classifier in a graphical form, as shown in Figure 4.

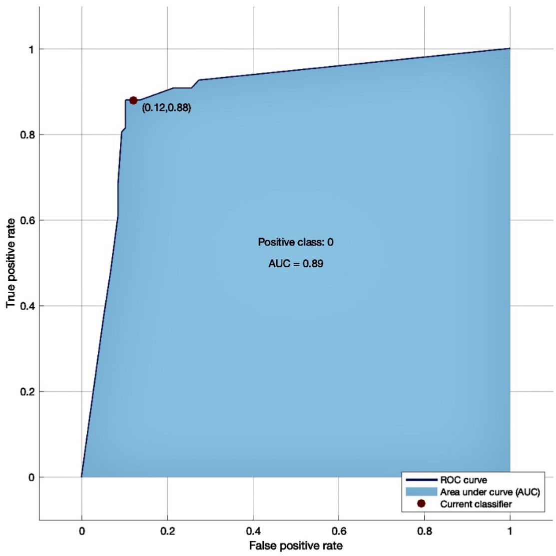


Figure 4: ROC curve of Boosted Trees for the first dataset.

Table 3
Confusion matrix of Linear Discriminant for the first dataset.

	Predicted Positive values	Predicted Negative values
True Positive Values	94 (True Positive)	14 (False Positive)
True Negative Values	22 (False Negative	95 (True Negative)

5.1.2. Linear Discriminant

It is a machine learning technique frequently used for predictive analysis (Xanthopoulos, Pardalos and Trafalis, 2013) (Balakrishnama and Ganapathiraju, 1998). As mentioned, in this study, we predict the impact of commuting based on the mode of commute using two datasets. Cross-validation was used to mitigate the risk of over-fitting. This approach ensured that the data was divided into five subsets, each serving as training and validation data in separate iterations. By rotating through the subsets, we obtained more reliable and robust performance estimates for our model (Moore, 2001). We achieved an accuracy of 84% using this classifier. This method correctly predicted 94 out of 108 for the first class. Similarly, 22 out of 117 were classified incorrectly for the second class. These graphical representations provide insights into the classifier's performance, as shown in Table 3 and Figure 5 below:

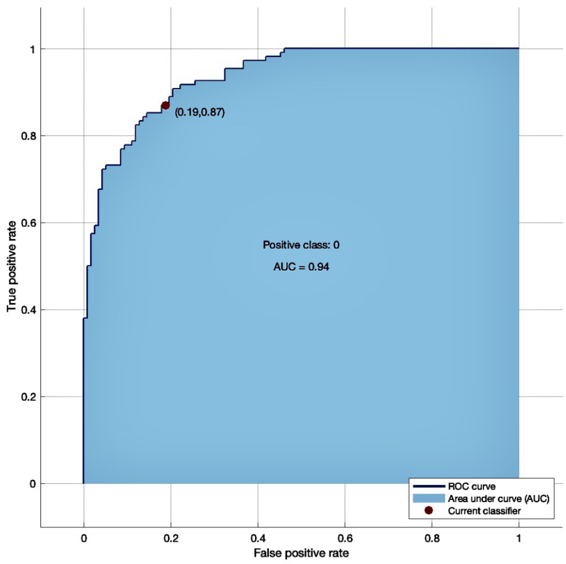


Figure 5: The ROC curve depicting the performance of Linear Discriminant for the first dataset.

5.1.3. Logistic Regression

It is also a popular machine learning algorithm in predictive analysis (LaValley, 2008) (Sperandei, 2014). We used this classifier to train both datasets. This classifier performed very well, with an accuracy of 84.44% for the first dataset. The model accurately predicted 92 out of 108 instances for the first class. Similarly, 19 out of 117 were classified incorrectly for the second class. The Confusion matrix and ROC curve obtained using this classifier are shown in Table 4 and Figure 6.

Table 4
Confusion matrix of Logistic regression for the first dataset.

	Predicted Positive values	Predicted Negative values
True Positive Values	92 (True Positive)	16 (False Positive)
True Negative Values	19 (False Negative	98 (True Negative)

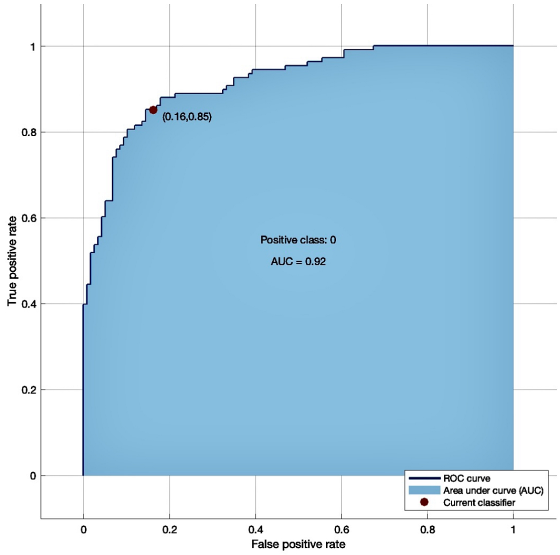


Figure 6: ROC curve of Logistic regression for first dataset

Table 5
Confusion matrix of Boosted Tree for the second dataset.

	Predicted Positive values	Predicted Negative values
True Positive Values	96 (True Positive)	12 (False Positive)
True Negative Values	8 (False Negative	109 (True Negative)

5.2. Using the main parameters of Blood pressure, Heart rate, EEG signals and personalized parameters

5.2.1. Boosted Tree

Similarly, the classifier was trained again using the second dataset. The second dataset was comprised of main parameters and personalised parameters. The dataset was partitioned into predictor and response variables to train the classifier using a five-fold cross validation approach. This process ensured that the data was divided into subsets and used for training and validation to enhance the model's performance and reliability. Adding those personalised parameters helped improve the model's performance to reach an accuracy of 91%. The model predicted 96 values correctly out of 108 for the first class. Similarly, only eight values were classified incorrectly for the second class out of 117. The confusion matrix and ROC curse have been plotted to show the model's overall performance, as shown in Table 5 and Figure 7 below.

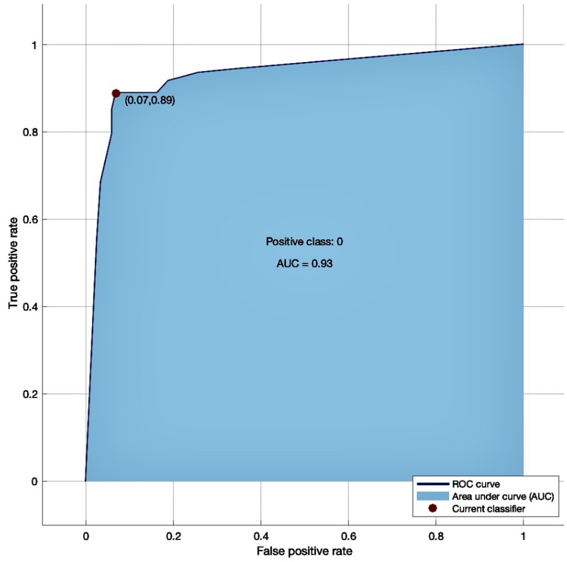


Figure 7: ROC curve of Boosted Trees for second data-set.

Table 6
Confusion matrix of Linear Discriminant for the second dataset.

	Predicted Positive values	Predicted Negative values
True Positive Values	94 (True Positive)	14 (False Positive)
True Negative Values	13 (False Negative	104 (True Negative)

5.2.2. Linear Discriminant

Likewise, the second dataset containing all personalised parameters was utilised to train the model. Initially, the dataset was classified into input and target variables and then trained using a five-fold cross validation technique to mitigate the risk of over-fitting (King, Orhobor and Taylor, 2021). Adding those personalised parameters helped to increase the model's performance with an accuracy of 88%. The model accurately predicted 94 out of 108 instances for the first class. However, for the second class, it classified 13 instances incorrectly out of 117. The overall performance of the classifier is shown in Table 6 and Figure 8 below:

5.2.3. Logistic Regression

Similarly, the performance of this classifier improved even further with the second dataset. The model achieved an impressive accuracy of 90.66%, making it the top-performing algorithm among the evaluated ones. A confusion matrix summarises the performance of all the selected machine learning algorithms (Patro and Patra, 2014). It also helps to prevent bias in prediction (Kaur and Malhotra, 2008). The model accurately predicted 94 out of 108 instances for the first class. In contrast, the second class misclassified seven instances out of the 117. The performance of the Logistic regression using the Confusion matrix and ROC curve has been demonstrated in Table 7 and Figure 9 Below.

5.3. Results of the PANAS questionnaire.

This study utilised a questionnaire form (PANAS) to gather commuters' feedback before and after their journey. The PANAS questionnaire holds major role in psychological assessment due to its ability to measure and distinguish between positive and negative emotional experiences. Its structured format and comprehensive set of items enable the assessment of an individual's current emotional state, aiding in clinical evaluations across various mental health conditions, including depression, anxiety, and mood disorders. PANAS serves as a valuable tool in research, allowing

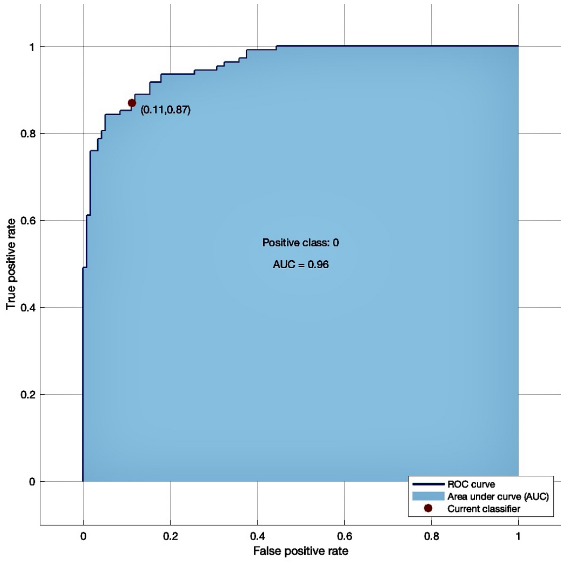


Figure 8: ROC curve of Linear Discriminant for the second dataset.

Table 7
Confusion matrix of Logistic regression for the second dataset.

	Predicted Positive values	Predicted Negative values
True Positive Values	94 (True Positive)	14 (False Positive)
True Negative Values	7 (False Negative	110 (True Negative)

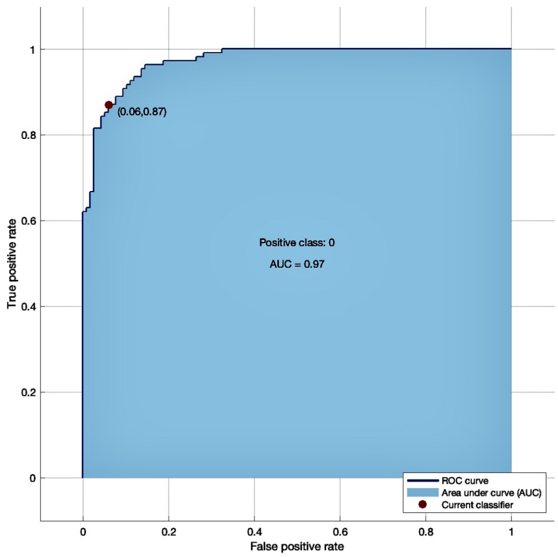


Figure 9: ROC curve of Logistic regression for the second dataset.

Table 8
Comparison of positive and negative affect before and after the commute.

	Positve Affect	Negative Affect
Avg Pre-Commute	34.73	11.16
Avg Post-Commute	28.60	19.05

for the exploration of emotional patterns, personality traits, well-being, and the effects of interventions on emotional states. Overall, the integration of qualitative research methods using the PANAS questionnaire, alongside objective measurements enhance the comprehensiveness and validity of the study's findings. By considering both subjective experiences and objective data, the research offers a holistic perspective on the effects of commuting modes on individuals' well-being, highlighting the importance of promoting healthier and more sustainable transportation options The form utilised in this study included a range of descriptive words that captured the participants' emotions and feelings, offering valuable insights into their subjective experiences within their environment. The PANAS scale employed for this purpose varied from 1 to 5, as depicted in Figure 1. Each participant completed the questionnaire before and after their journey. Based on the responses from the questionnaire, we computed the scores of positive and negative, as presented in the provided Table 8. The scores obtained from the PANAS questionnaire range from 10 to 50, with bigger values indicating increased levels of affect experienced by the participants.

After summing the positive and negative affect scores, average values for positive and negative affect scores both before and after their journey were determined. The results are presented in the provided Table 8.

The analysis of PANAS results revealed that participants exhibited higher levels of positive affect before and after commuting. This finding indicates that participants' moods and emotional states tended to be more positive before their commute. Likewise, the results showed that participants experienced higher levels of negative affect after commuting, suggesting increased stress among participants following their commute.

6. Analysis and Critical Review

This study provides an insightful examination of how commuting impacts an individual's physical state, focusing on leveraging machine learning for stress prediction. By employing biometric data such as heart rate, blood pressure, and EEG signals, the research contributes to the growing field of automated health monitoring, particularly relevant in today's increasingly urbanised and high-pressure environments. The approach holds significant potential for improving public health by offering a scalable way to monitor stress levels, which traditionally requires medical expertise and subjective self-reporting methods.

In this research, a comprehensive experiment was conducted to choose the most effective machine-learning technique to predict the impact of commuting. We selected three algorithms based on a comprehensive literature review to accommodate the diversity in data types. Specifically, we employed both linear (linear discriminant and logistic regression) and non-linear methods (boosted trees). Linear models offered an interpretable framework, balancing performance with the ability to understand the direct relationship between each factor and stress. In contrast, non-linear models like boosted trees allowed us to capture complex interactions and non-linear effects, offering a complementary perspective on the data. This dual approach enabled us to assess which model type best captured the relationships among variables, providing a more comprehensive understanding of the data and facilitating a selection that balanced performance with interpretability. Including personalised parameters enhanced the model's accuracy, demonstrating the importance of considering individual-specific variables as illustrated in Table 9.

The analysis revealed a significant increase in physiological signals after commuting, irrespective of commute duration. Notably, the Boosted Trees model outperformed other approaches, achieving 91.11% accuracy. These findings suggest a clear connection between passive commuting and elevated stress levels, supporting previous research that links passive commuting to negative emotional states. The boosted Trees model achieved promising results for both data sets: the first dataset had main parameters (BP, HR and EEG), and the second contained main and personalised parameters. The confusion matrix was employed to assess the performance of all techniques, which provided a comprehensive overview of how well the methods correctly classified the instances and identified any misclassifications, as shown in Table 9. Also, to address concerns about overfitting due to potential data leakage, we applied the five-fold cross validation method with a specific strategy aimed at preventing subject-wise data leakage. This strategy, known as grouped five-fold cross validation ensured that data from a given participant did not appear

Table 9
Performance of machine learning techniques using various performance metrics.

Techniques	Dataset	Accuracy with 5-fold cross validation	Accuracy without validation	Precision	Recall
Boosted Tree	Dataset I	88.00%	89.2%	0.87	0.87
	Dataset II	91.11%	91.80%	0.88	0.92
Linear Discriminant	Dataset I	84.00%	84.6%	0.87	0.81
	Dataset II	88.00%	88.8%	0.87	0.87
Logistic Regression	Dataset I	84.44%	85.20%	0.85	0.92
	Dataset II	90.66%	91.40%	0.87	0.93

in both training and validation sets within any fold. By isolating each subject within folds, we maintained statistical independence and avoided introducing bias due to repeated subject data. Five-fold cross validation reduces overfitting risks by training and validating across multiple folds, which exposes the model to a variety of data distributions and reduces dependency on a single train/test split. This iterative approach helped us identify and control for patterns that could lead to overfitting. In this research, we compared results obtained with and without cross-validation, further demonstrating the effectiveness of this approach in preventing overfitting.

Similarly, one of the limitations of this study is the small dataset, which may limit the generalizability of the results. With fewer samples, the model can be prone to over-fitting, potentially capturing noise rather than the underlying patterns. Additionally, the health status of cyclists, who tend to be healthier overall, may have confounded the results, suggesting that they experienced less stress. To mitigate this issue, we employed cross-validation to ensure more reliable performance estimates and used regularisation techniques to control model complexity. In Figure 10, the performance of the different machine learning models when we employed the cross-validation method. Similarly, Figure 11 shows the performance of different machine learning models without cross-validation for both datasets.

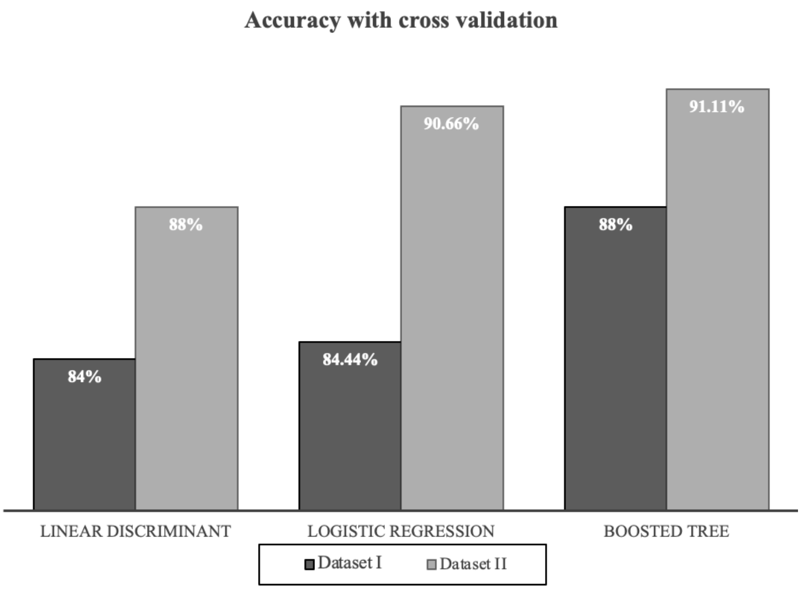


Figure 10: Classification accuracy for Machine learning techniques for both datasets with Five-fold cros validation.

7. Conclusions

This study developed different machine learning algorithms to analyse and understand how commute-related factors impact individuals. Linear Discriminant Analysis, Boosted Trees, and Logistic Regression were trained on

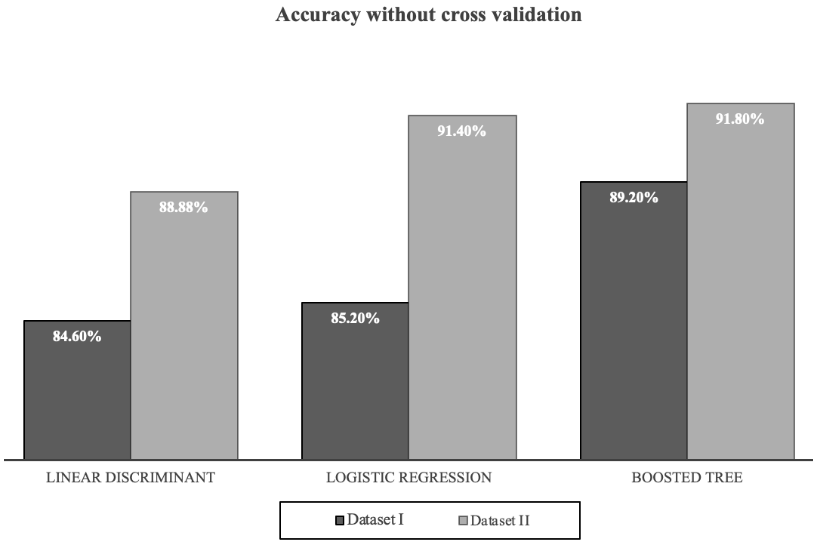


Figure 11: Classification accuracy for Machine learning techniques for both datasets without validation.

two datasets: one containing key parameters such as blood pressure (BP), heart rate, and EEG signals, and another incorporating personalised factors like age, weight, commute duration, and weather conditions. These datasets provided a comprehensive view of how commuting affects human well-being. The Boosted Trees model performed best, with accuracies of 88% and 91.11% for the two datasets. Adding personalised parameters improved the performance of all machine learning models, reinforcing that passive commuting modes are more stressful than active ones. These findings support advocating for active commuting modes to reduce stress and enhance well-being.

The research employed the PANAS (Positive and Negative Affect Schedule) questionnaire to gather participants' subjective perceptions of their commute. Results from the PANAS responses showed that commuting increased negative emotions, particularly after passive commutes like driving, where participants reported higher levels of negative affect. In contrast, active commuters, such as cyclists, experienced less stress. Notably, the negative impact of passive commuting was consistent regardless of commute duration, highlighting that mode of transport, rather than the length of the commute, plays a significant role in affecting emotional well-being.

This research presents a comprehensive approach that combines advanced machine learning techniques with both objective physiological data and subjective self-reported emotional states to examine the effects of commuting on well-being. The study distinguishes itself by analyzing a range of commute-related factors, including personalized variables such as age, alcohol consumption, and commute duration, alongside key bio-signals such as heart rate and blood pressure. The integration of the PANAS questionnaire adds a psychological dimension, enabling the study to capture a holistic view of the commuter experience. Beyond achieving high accuracy in predicting stress levels with models like Boosted Trees, the research reveals the distinct impacts of passive and active commuting modes, independent of commute length. This application of machine learning for real-time stress detection through bio-signals positions the study as a foundational step toward the development of intelligent, health-focused transportation systems that integrate urban planning with health monitoring.The study's contributions span fields s uch a s u biquitous c omputing, body sensor technology, and wireless telehealth. By highlighting the unique effects of passive versus active commuting, this research opens pathways toward autonomous systems capable of continuous stress monitoring, encouraging healthier commuting behaviors and potentially mitigating related health risks. Overall, this research contributes to advancing sustainable transportation systems by promoting healthier commuting modes, with potential applications in urban planning and public health.

8. Data availability statement

The data used to support the findings of this study are currently under restriction while the research findings are commercialised. Requests for data after publication of this article will be considered by the authors.

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