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MACHINE LEARNING APPROACH FOR MULTI-CLASS STRESS ASSESSMENT WITH ELECTROENCEPHALOGRAPHY SIGNALS

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Abstract
This paper focuses on utilizing Electroencephalography (EEG) signals and machine learning techniques in developing an objective stress assessment framework. The study aimed to investigate the correlation between EEG and Perceived Stress Scale (PSS) by utilizing data segmentation technique. The PSS scores are employed to record perceived stress levels of individuals. These PSS scores serve as the basis for categorizing the data into three classes: i) two class: stressed and non-stressed ii) three class: stressed, mildly stressed, and non-stressed, iii) four class: highly stressed, moderately stressed, mildly stressed and non-stressed. EEG recordings are captured from 40 participants using 4 channels Inter axon Muse headband, equipped with dry electrodes. The EEG data is segmented into units of 10 seconds. The data is processed to extract five feature sets including Power Spectrum, Rational Asymmetry, Differential Asymmetry, Correlation and Power Spectral Density. The success levels are accessed utilizing classifiers (Naive Bayes, Support Vector Machine, Logistic Regression, Simple Logistic Regression, Random Tree, K-Nearest Neighbor, Bagging, Random Forest, Multilayer Perceptron, AdaBoost). The highest accuracies achieved for two-, three-, and four-class stress classification are 91.52%, 88.47%, and 87.36%, respectively. These accuracies are obtained using the Adaboost classifier for two-class classification, the Random Forest classifier for three-class classification, and the Adaboost classifier again for four-class classification. These findings underline the importance of the chosen features and classifiers in increasing the prediction accuracy while contributing to the existing knowledge on stress detection with EEG Signals.

Keywords: EEG; PSS; Stress Detection; Machine Learning; Classification; Physiological Data

1 Introduction

Rapid transformations in the society and development of technology introduce inevitable stressors into daily life. In humans, emotions can be classified into two categories: negative emotions and positive emotions [1]. Stress is rooted in negative emotions that can trigger other emotions, such as sadness or anger. A stressful event can cause the heart to beat faster, respiration to hasten, and muscles to tighten etc. Along the years, scientists have not only discovered the mechanisms and reasons behind these effects but also deepened their understanding on the long-term consequences of stress on both physical and mental well-being. Overtime, continuous activation of the stress related issues can have detrimental impacts on the body. In order to prove this, Selye performed numerous experiments on animals, subjecting them to various emotional and physical stressors such as extreme heat or cold environments, and also by creating frustrations in different ways. Stress in humans can be categorized into various types based on the symptoms and duration of the stress. One type of stress that individuals encounter in their everyday life is perceived stress [2].

Perceived stress is a long-standing condition that can arise from social factors such as unsatisfactory career, unhappy marriage and financial hardship [3]. Perceived stress effects vary greatly among individuals as each person has unique mechanisms to cope with the situation and resilience levels. Factors such as personality traits, social support, and previous experiences can impact how one perceives stress. Taking perceived stress into account is crucial while evaluating an individual's overall stress level. This will provide insight about their reactions and coping strategies in response to various stressors [4, 5].

Stress can be measured by physiological measures of stress in humans are crucial because they can address the issue of inaccurate self-reporting by individuals. This is due to the fact that physiological measures rely on measurements of hormones, brain function, blood circulation, and other factors through sensors that are beyond human control and cannot be falsely manipulated. To measure a person's response, sensors are attached to the individual's body. In humans, there are two components of Autonomic Nervous System (ANS): the Parasympathetic Nervous System (PNS) and the Sympathetic Nervous System (SNS) [2]. while experiencing stress, variations occur in the human ANS which results in an increase of SNS activity and decrease in PNS activity. Nerve Cells in human brain are responsible for processing and transmitting chemical and electrical signals. Signals resulted in firing of neurons are recorded by EEG. The process of data collection and annotation is a crucial component in the framework for recognizing human stress. High-quality data is essential for conducting a reliable and robust analysis of stress levels. To achieve this, a well-designed experiment following standard protocols is necessary. The measured EEG signals are then interpreted using machine learning algorithms. An efficient machine learning model requires critical feature extraction and selection. Feature extraction involves obtaining meaningful attributes from the collected data resulting in a feature vector used as an input for the classification stage. These features are characterized in various ways, such as unimodal versus multimodal features[6], linear versus non-linear features [7] and wavelet or time [8] or frequency [9] domain features. The computational complexity of these features can vary from simple statistical measures like maximum, minimum, median and mean to more intricate features based on specific modalities. Each sensor is used to extract a unique set of features for stress recognition in humans[10].

It is aimed to devise a new approach for stress identification using EEG signals that addresses above challenges and offers a more precise, resilient, and computationally efficient solution. The proposed approach will incorporate advanced signal processing techniques, inventive feature extraction methods, and modern machine learning algorithms to achieve superior stress identification performance. Furthermore, the approach will be adaptable to various situations, such as different stressors, EEG channel configurations, and individual variability. The resulting methodology will demonstrate improved performance compared to the existing techniques in terms of accuracy, dependability, and computational efficiency hence ultimately contributing to the progress of stress identification technology and its application in healthcare, education, and other sectors [11].

2 Materials and Techniques

The process of stress recognition using EEG involves collecting and analyzing brainwaves data to detect stress patterns. A group of 40 participants was recruited and asked to fill PSS form. Four stages of capturing the EEG data such as acquisition, pre-processing, feature extraction and selection and classification are shown in the Fig. 1.

Figure 1: Framework for Assessing Human Stress Using EEG Signals

2.1 EEG Data Acquisition

In the experiment, 40 healthy participants took part, 20 males and 20 females, with ages ranging from 18 to 40 years. The standard deviation and average age were σ = 6:69 and μ = 24:85, respectively. All participants had a minimum of 12 years education and were affiliated with a university, either as students or as instructors. All the participants involved were Asian with no mental or physical illnesses.

2.1.1 Apparatus

In this study, the Muse headband by InteraXon Inc. was employed for EEG data acquisition. This versatile and easy-to-wear EEG signal recording system allows for convenient headset wear during public speaking activities [30]. The Muse headband features four dry electrodes at positions AF7, AF8, TP9, and TP10, and a reference electrode at position Fpz [31] depicted in Fig. 2. Data was recorded at a sampling rate of 256 Hz. The smartphone device connected via Bluetooth (Huawei Mate 10 Lite with 4 GB RAM) running the Muse monitor application recorded data and transferred it to a PC for further offline processing. The Muse headband and its electrode were placed according to the 10-20 electrode positioning system. EEG signals were recorded from each participant for three minutes.

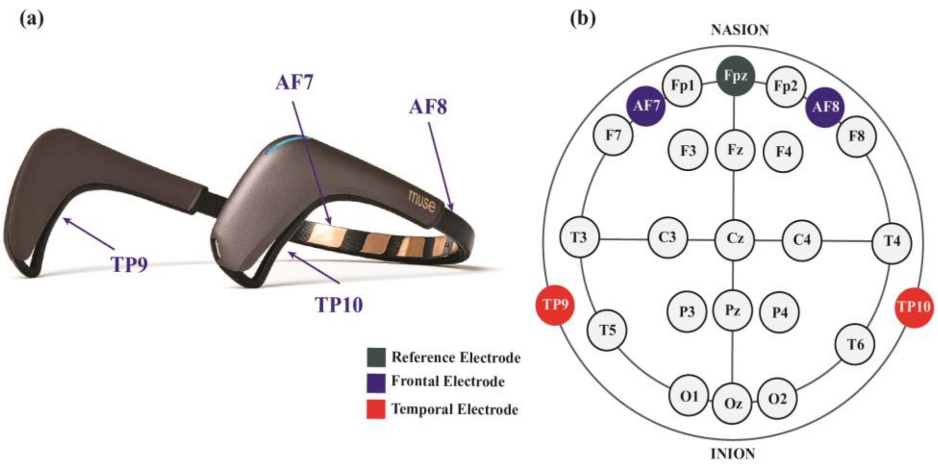


Figure 2: EEG Recording Apparatus (a) Muse Headset (b) Electrode Positioning on Scalp

2.1.2 Experimental Procedure

All the participants were guided about the experimental procedure and were made to sit in a calm, temperature-controlled space with regular lighting conditions. After signing a consent form the proper experiment started and initially the participants were asked to fill in the demographic questionnaire (bio data sheet) which includes information about their age, gender, and history of any mental illnesses. Later, the subjects were instructed to complete PSS questionnaire, created by professional psychologists, to evaluate the perceived stress levels. This 10-item questionnaire calculates the amount of stress a person experienced over the last 30 days. On a scale of 0 to 4, the subjects could respond to each question, with 0 for no stress experience and 4 for frequent experience over the past 30 days [32]. The total PSS ranges from 0 to 40, depending on how well the subjects answered each question. After gathering the questionnaire results, each subject was classified according to its obtained PSS score. In the end, EEG data was recorded for three minutes with open eyes in a relaxed position while sitting.

2.1.3 Pre-Processing

The EEG data acquired from the subjects was initially processed prior to the stage of feature extraction and categorization. To minimize the noise in the recorded EEG signals, an onboard DRL feedback mechanism was utilized [33]. The purpose of DRL circuits was to ensure the good contact between EEG electrodes and the skin. By thresholding characteristics like mean power, power standard deviation, peak amplitude, amplitude standard deviation, amplitude kurtosis, and amplitude skewness of the EEG signal, a clean signal can be obtained [34]. However, the Muse headband used in this study had a built-in noise reduction feature which determined the EEG signal as clean as if the incoming signal exhibited variance, amplitude, and kurtosis values below a certain predefined threshold [35]. The frequency bands of the EEG, including delta (0–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–50 Hz), were acquired through the Muse headband's internal digital signal processing unit. This processing unit applies Fast Fourier Transform to the raw EEG signals with 90% overlap on a window size of 256.

2.2 Feature Extraction and Selection

The interpretation of the collected EEG data involved the extraction of five feature sets from each frequency band at each channel. These four features are; Power Spectrum (PS) [36], Rational Asymmetry (RASM) [37], Differential Asymmetry (DASM) [38], Correlation (CR) [39] and Power Spectral Density (PSD) [40]. PS represents the average absolute power across four scalp electrodes in the five EEG signal frequency bands. PS consists of twenty features (five for each channel). RASM signifies the ratio of the absolute power between asymmetrical channels in the left and right brain hemispheres [41]. A total of ten RASM features, five from each band for each pair, were obtained. DASM is the disparity between the absolute power of asymmetrical channels in the left and right brain hemispheres [42, 43]. For this, a total of ten DASM features - five from each band for each pair were attained. CR measures how two variables change with respect to each other [44]. In this reported work, CR between asymmetrical channels for the brain left and right brain hemispheres was computed. Specifically, CR between electrode pairs (TP9, TP10) and (AF7, AF8) were evaluated. This yielded a total of ten values - five from each frequency band for each pair. The PSD outlines the power spread of the signal over specific frequencies. Here, Welch method [45] was utilized to compute the PSD with 50% overlap. The mean and variance of the PSD from each band

and channel were taken as features, resulting in 720 values from four channels and five bands. Wrapper methods was used for feature selection [46].

2.2.1 Wrapper Method

The wrapper method is a feature selection mechanism that 'wraps' the learning model, scrutinizing various feature assortments to find the one that enhances model performance the most [47]. The classifier is trained multiple times by utilizing feedback from each iteration to choose a subset of features for subsequent iterations. While these methods are more computationally intensive than embedded methods, they eliminate the data points that poorly discriminate between class labels when evaluated individually [48].

2.3 Classification Algorithms

In the current study, the assessment of stress in humans has utilized various classifiers with supervised learning techniques being the most commonly used in the literature. Vapnik's development of Support Vector Machine (SVM) is a popular linear classifier that has demonstrated success in stress classification [49]. The SVM algorithm works by determining a linearly separating hyperplane in a higher dimension through the use of support vectors [50]. The K- NN algorithm is a straightforward classifier that learns from individual instances, where training instances are retained in their original form. A distance function is employed to calculate the distance between training instances and a test instance. The classification of the test instance is determined by the nearest training instance based. The logistic regression (LR) model with an initial ridge estimator was developed by le Cessie and van Houwelingen [51]. It prevents overfitting by penalizing large coefficients. Naïve Bayes (NB) classifiers necessitate several constraints and are linear concerning the number of features in a learning problem. NB is a probabilistic classifier that relies on Bayes' theorem. It employs the maximum posteriori hypothesis from statistics and performs effectively with high-dimensional input data. NB is a nonlinear classifier that delivers satisfactory results in real-world situations. A Multi-Layer Perceptron (MLP) is a type of neural network consisting of multiple layers of neurons. Neurons in each layer are connected to the neurons in the adjacent layers with each connection having a specific weight that influences the response of neurons in the subsequent layer [52, 53]. A Random Tree (RT) belongs to the decision tree family. Decision trees are tree-shaped structures that enable effective decision-making by iteratively dividing data into subsets according to input feature values. The Random Tree algorithm builds a tree by selecting K random attributes at each node through a probabilistic process without implementing any pruning. The Random Forest (RF) classifier [54] utilize multiple decision trees during the training process and produce an average prediction from the individual tree. Standard decision tree algorithms rely on a set of rules for dataset prediction and are rule-based. In contrast, random forest classifier randomly determine the root node and feature splits instead of using the gini index [55] or information gain for root node calculation. The decision process involves a majority vote, selecting the most frequently occurring class among these outputs. Consequently, the classifier's output is the class that has garnered the most votes [56]. The bagging classifier algorithm utilizes various subsets of data from the datasets while dividing them into training and testing data. This algorithm generates multiple predictions or probability values which are then voted upon to derive a single real value [57]. Its numerous samples from the initial dataset. These samples then undergo a specific algorithm within the classifier that forms the core of the bagging classifier process. Several predictions or probability values are generated and the one with the majority vote becomes the overall prediction or probability value for the entire process. The AdaBoost algorithm is designed to optimize the classifier performance. The core concept of AdaBoost is that a weak learning algorithm, which performs marginally better than random guessing, can be transformed into an exceptionally accurate and powerful learning algorithm [58]. The final model is essentially a weighted consensus of all weak learners.

3 Experimental Results

3.1 Data Labelling

According to the PSS score, participants were classified into three classes as: (i) non-stressed and stressed, (ii) non-stressed, mildly stressed and stressed, (iii) non-stressed, mildly stressed, moderately stressed and highly stressed. The two and three class stress classification, based on the PSS score mean value and standard deviation, is a common practice in numerous stress measurement studies [12-14] and particularly in the study by the authors who proposed the PSS questionnaire[15]. For two class stress classification, participants with scores equal or lower than 20 were marked as non-stressed, while those with scores higher than 20 were considered stressed. In the three-class stress classification, participants were divided into three groups. Subjects with PSS score between 0 and ($\mu PSS - \sigma PSS/2$) were labeled as non-stressed, those with a PSS score between ($\mu PSS - \sigma PSS/2$) + 1 and ($\mu PSS + \sigma PSS/2$) - 1 were labeled as mildly stressed and those with PSS score ranging from ($\mu PSS + \sigma PSS/2$) up to 40 were identified as stressed [3]. Following this scheme, 12 participants were labeled non-stressed, 17 were mildly stressed, and 11 were identified as stressed.

In four class stress classification, the participants were divided into four groups. The non-stressed group consisted of individuals with score less than ($\mu - \sigma$), corresponding to PSS score below 15. The Mildly Stressed category included individuals with score between ($\mu - \sigma$) and μ, representing PSS score ranging from 15 to 22. The Moderately Stressed group comprised participants with scores ranging from μ to ($\mu + \sigma$), reflecting PSS score between 22 and 29. Highly Stressed group included participants with scores greater than ($\mu + \sigma$), indicating PSS score above 29. Here, 8 participants were classified as non-stressed, 14 as mildly stressed, 10 as moderately stressed, and 8 as highly stressed.

3.2 Feature Selection and Performance Analysis

3.2.1 Two-Class Stress Classification

The AdaBoost M1 model results indicated a strong performance with an overall accuracy of 91.53%. Of the total 720 instances, the model incorrectly classified 61 instances with an error rate of 8.47%. The kappa statistic of 0.8282 suggested that the model's agreement with the actual classes is considerably beyond chance hence had a good level of prediction reliability. Examining the detailed accuracy by class, the model showed slightly better performance on "stressed" instances with a TP rate of 0.939 compared to the "non-stressed" instances with a TP rate of 0.886. In addition, the model demonstrated strong precision, recall, and F-measure scores for both classes hence reinforcing its effective predictive capacity (Fig. 3).

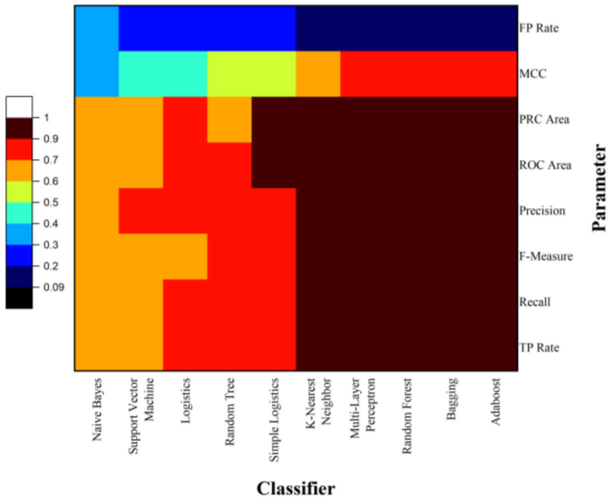
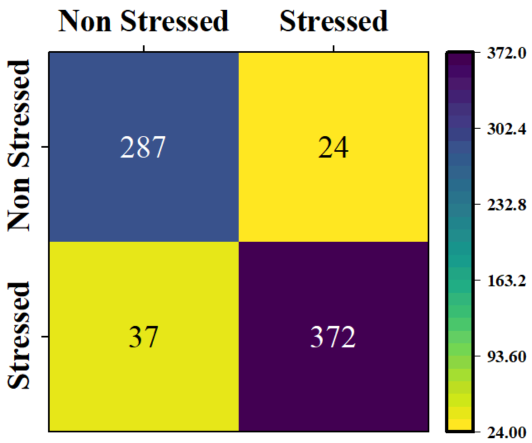


Figure 3: Heatmap for Two-Class stress classification: X-axis illustrates classifiers, while y-axis represents parametric adjustments. Color bar in heatmap signify variations in parameters

The confusion matrix further elaborated on the performance, where the model classified 287 out of 324 instances correctly as "no-stressed" and misclassified 37 instances (Table 1). For the "stressed" class, the model performed even better by correctly classifying 372 out of 396 instances and incorrectly classifying 24. The relatively higher TP rate and lower FP rate for the "stressed" class suggest that the model was more adept at identifying "stressed" instances compared to the "non-stressed". These results overall indicated a robust classification capability of the AdaBoost M1 model in this scenario.

Table 1: Confusion Matrix for AdaBoost classifier for two class classification



3.2.2 Three-Class Stress Classification

The Random Forest model correctly classified 637 out of 720 instances, equating to an overall accuracy of 88.4722%. This superior performance is reinforced by the kappa statistic of 0.8223. Despite its strong classification performance, the model exhibited a relatively high MAE of 0.2472 and RMSE of 0.305. The RAE and the RRSE were 56.7049% and 65.33% respectively (Fig. 4). Class-specific performance of the model was also remarkable, with the "mildly stressed" class experiencing the highest TP Rate at 0.935. Both "non-stressed" and "Stressed" classes had TP rates above 0.84. FP rates were minimal for all classes, indicating that the model did not misclassified instances frequently. The model's precision, recall, F-Measure, and MCC all exhibited high values and hence suggested that the model's predictions were reliable across all the classes. Furthermore, all classes had ROC area values above 0.958 which signified excellent class discrimination capabilities.

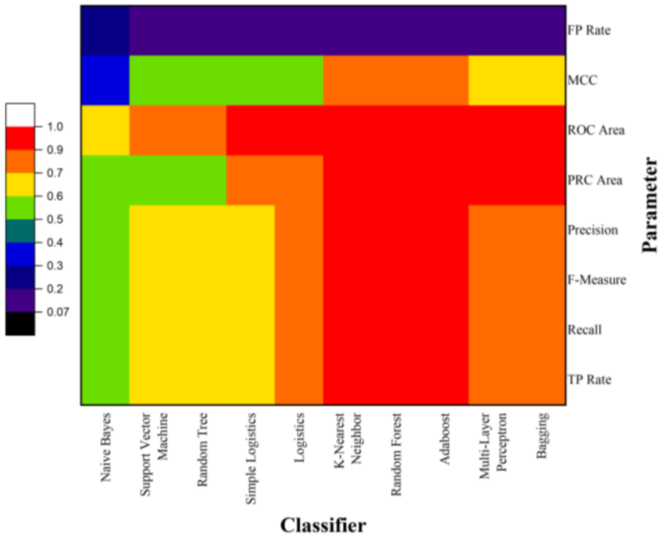


Figure 4: Heatmap for Three-Class stress classification: X-axis illustrates classifiers, while y-axis represents parametric adjustments. Color bar in heatmap signify variations in parameters

Likewise, high PRC area values attested the model's solid performance in balancing precision and recall. The confusion matrix reveals that most misclassifications occurred between the "non-stressed" and "mildly stressed" classes, as well as between the "stressed" and "mildly stressed" classes (Table 2). Overall, the Random Forest model exhibited robust performance in classifying instances into all three categories.

Table 2. Confusion Matrix for Random Forest classifier for three class classification

	Stressed	Mildly Stressed	Non Stressed
Stressed	169	10	9
Mildly Stressed	22	286	25
Non Stressed	7	10	182

3.2.3 Four-Class Stress Classification

The AdaBoost M1 classifier with the J48 decision tree as the base classifier gave highest accuracy of 87.3611%. A kappa statistic of 0.8273 also indicated excellent agreement between the model's predictions and the actual values. Moreover, the model showed relatively small error rates, with MAE of 0.0637 and RMSE of 0.2481. The RAE of 17.3239% and RRSE of 57.8853% confirmed the model's strong predictive capacity.

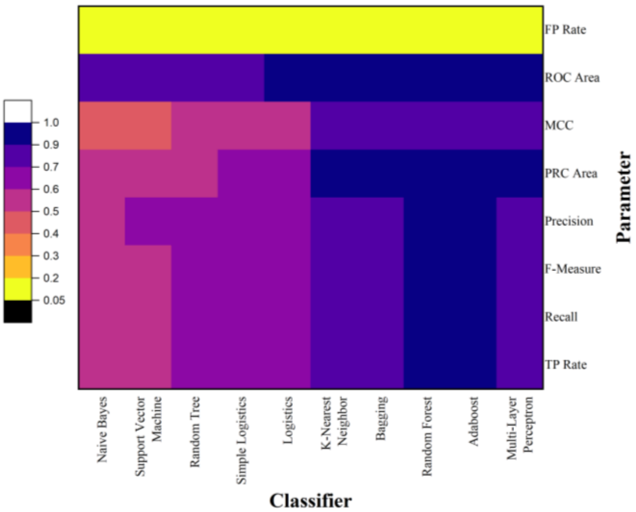
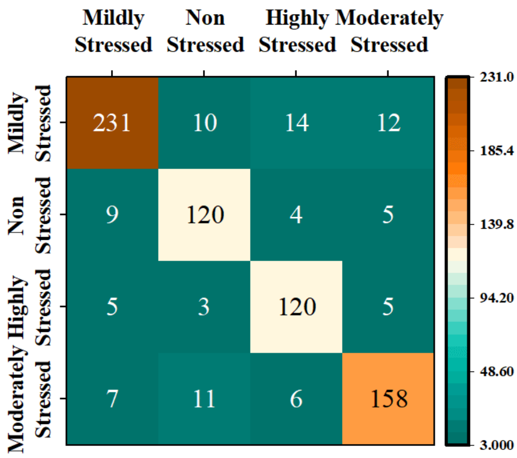


Figure 5. Heatmap for four-Class stress classification: X-axis illustrates classifiers, while y-axis represents parametric adjustments. Color bar in heatmap signify variations in parameters

The classifier showed a balanced performance across all stress classes in the detailed accuracy by class with TP rates ranging from 0.833 (Non-Stressed and Highly Stressed) to 0.917 (Mildly Stressed). Precision rates, indicated the correctness of the model's positive predictions, were also quite high for all the classes, reaching up to 0.902 for the "Highly Stressed" class (Fig. 5). Confusion matrix elucidated how well the model performed for each class (**Table 3**). The highest number of instances were correctly classified in the "Mildly Stressed" class (231 instances), while the "Non Stressed" class had the least (120 instances). Misclassifications, although less common, mostly occurred between "Mildly Stressed" and "Non Stressed", "Mildly Stressed" and "Highly Stressed", and "Moderately Stressed" and "Mildly Stressed".

Table 3. Confusion Matrix for AdaBoost classifier for four class classification



In summary, the AdaBoost M1 classifier demonstrated excellent performance for this four-class stress detection problem among all other classifiers used in study.

4 Discussion

In this study, 10 different classifiers were used for two-, three- and four class stress classification. The training and testing of classification algorithms were conducted using weka tool. The overall accuracy of classifiers is presented in Fig. 6. Notably, the highest accuracy for two-, three- and four class stress classification was achieved by adaboost, random forest and adaboost respectively. An accuracy of 91.53% with F measure of 0.915 was achieved two class stress classification. For three class stress classification, the maximum accuracy of 88.47% with F measure of 0.884 was attained.

For four class stress classification, an accuracy of 87.36% with F measure of 0.873 was achieved. The precision and recall were highest for the Adaboost, Random Forest, and Adaboost classifiers in two, three, and four-class stress classification. The confusion matrices also revealed the above trend: in two-class stress classification, 287 out of 324 non-stressed subjects and 372 out of 396 stressed subjects were correctly classified. In four-class stress classification, 120 out of 144 non-stressed subjects, 231 out of 252 mildly stressed subjects, 158 out of 180 moderately stressed subjects, and 120 out of 144 highly stressed subjects were correctly classified. In three-class stress classification, 182 out of 216 non-stressed subjects, 286 out of 306 mildly stressed subjects, and 169 out of 198 stressed subjects were correctly classified. The obtained results had shown varying levels of accuracy with different classifiers. While, a comparison with literature revealed a rich blend of methodologies, models, and features employed by various researchers in the past. However, from literature it was revealed that a range of other classifiers were also used. For example, C.K. Alfred & C. Chia employed Linear Discriminant Analysis (LDA), K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) classifiers and achieved a maximum classification rate of 72% through KNN with Discrete Cosine Transform (DCT) [16]. Likewise, Saeed et. al. utilized the Naive Bayes algorithm and achieved an accuracy of 71.4% in stress level classification [17]. The present study achieved notable stress classification accuracy for 40 subjects in two-class classification, surpassing various previous studies conducted [7, 18-22]. Additionally, the current scheme outperformed previous methodologies in three-class stress classification [23]. Whereas, Arsalan et. al. managed to achieve 64.28% accuracy for three-class classifications utilizing similar set of classifiers and highlighting the potential variability in performance across different datasets and stress detection approaches [3]. Saeed et. al. demonstrated that correlation-based feature subset selection techniques combined with neural oscillations improved the stress classification accuracy to 78.57% [19].

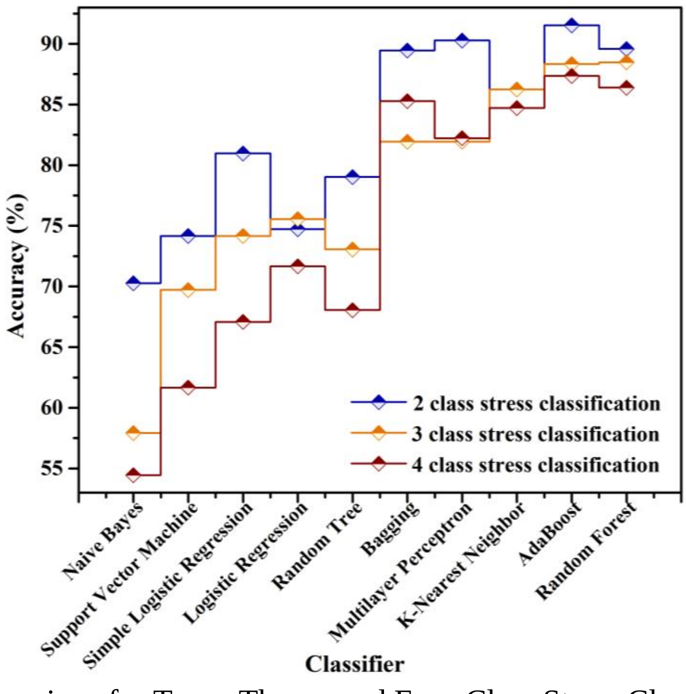


Figure 6: Accuracy comparison for Two-, Three-, and Four-Class Stress Classification: The y-axis represents classifiers, while accuracy is displayed on the x-axis. Blue, Orange and Purple color indicates stress classification for Two, Three and Four-class respectively

These findings closely align with the AdaBoost findings for the 3-class classifier in the current study. Similarly, Jebelli et. al. reported an accuracy of 71.1% by utilizing support vector machine learning algorithm [24] which again mirrors the findings of the present study. Nagar & Sethia also corroborated the results of the current study by highlighting the effectiveness of the KNN algorithm in classifying stress with 74.43% average classification accuracy [25]. Arsalan et. al. reported 75%

accuracy rate with MLP classifier [22]. This accuracy rate is slightly lower than the corresponding results in the present study.

Previous studies have shown that the stress detection utilizing EEG signals is feasible and effective. A. Hamid et. al. and Hambali et. al. found correlations between EEG signals and stress levels as measured by the PSS [26, 27]. Similar to this, the findings from the current study stand comparatively well against the findings from the literature for both two- and three-class stress classification. Nevertheless, some studies exhibited even higher accuracy levels as Saeed et al achieved stress classification accuracy of 85.20% through Support Vector Machines and alpha asymmetry [28]. In terms of features, the current study leveraged a varying number of attributes for different classifiers. These attributes consisting of several distinct features ranging from 20 to 30 in the two-class stress classifier system and from 14 to 28 in the three-class stress classifier system. Whereas, other studies had explored the use of various distinctive features such as alpha and beta asymmetries [28] Electroencephalography based Classification of Long-term Stress using Psychological Labeling, low beta waves [17], or EEG-based connectivity patterns [29]. It should be noted that while the results of the present study are promising, the literature survey revealed a myriad of methodologies employed for stress detection. Each study targeted a different aspect of stress and leveraged different features, classifiers, or number of attributes. The differences in the obtained results highlight the importance of considering factors such as diversity of the study population, types of stressors used, choice of classifier, and features selected. However, current research makes novel contribution by successfully implementing a four-class stress classification system utilizing EEG data. This breakthrough goes beyond the confines of traditional stress classification studies, providing a pathway to explore intricate stress-related patterns and variations. The absence of prior research in this domain underscores the significance of current study, which serves as a pivotal point for future research.

5 Conclusion

The Alpha, Beta, Gamma, Delta, and Theta bands of EEG signals have been used to study primarily the binary and multiclass stress classification with the features Power Spectrum, Rational Asymmetry, Differential Asymmetry, Correlation and Power Spectral Density. This analytical investigation enables us to achieve classifying the Stress Levels in individuals. These features were extracted from EEG data segments with a duration of 10 seconds. A wrapper method was used to select the features that contributed the most to the classification accuracy. The stress level was accessed utilizing parametric (Naive Bayes, Support Vector Machine, Logistic Regression, Simple Logistic Regression) and non-parametric (Random Tree, K-Nearest Neighbor, Bagging, Random Forest, Multilayer Perceptron, AdaBoost) classifiers. It was noted that the findings highlighted the effectiveness of AdaBoost and Random Forest classifiers in predicting the classes. The highest accuracies achieved for two-, three-, and four-class stress classification were 91.52%, 88.47%, and 87.36%, respectively. These accuracies were obtained using the Adaboost classifier for two-class classification, the Random Forest classifier for three-class classification, and the Adaboost classifier again for four-class classification. These findings underline the importance of the chosen features and classifiers in increasing the prediction accuracy while contributing to the existing knowledge on stress detection with EEG signals.

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Ethics Approval: The experimental setup was designed in compliance with the declaration of Helsinki and was authorized by the Directorate of Advanced Studies Research and Technological Development (ASR&TD) at UET Taxila.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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