Detecting Changes in Stress Levels in University Students Using EEG Asymmetry

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***Abstract*—University students are vulnerable to the adverse effects of stress on their physical and mental well-being, leading to growing interest in the ability to monitor stress levels. This study used a noninvasive electroencephalogram to monitor changes in stress in a real classroom. We examined asymmetrical changes in the EEG spectra in the theta, alpha, beta, and gamma frequency bands to assess the changes in the participants' stress levels. The differences in EEG asymmetry between increased and decreased stress levels were statistically significant in the alpha band at F3/F4 and in the beta band at FP1/FP2. This study further demonstrated the feasibility of using machine learning classifiers to identify changes in stress levels by analyzing EEG asymmetry recorded from only two or four EEG channels.**

***Index Terms*—stress, EEG, classroom, channel pairings, asymmetry, alpha, beta**

I. Introduction

Stress is a biological phenomenon extensively studied in various academic fields, including psychology, cognitive science, biomedical engineering, and others. While everyone experiences stress, university students are much more susceptible to stress-related disorders [1]. Stress can have a wide range of negative impacts, including detrimental effects on physical and mental health [2]. For example, a study involving 288 nursing students demonstrated that stress was directly correlated with psychological symptoms [3]. This study uses an electroencephalogram (EEG) to quantify stress-level changes experienced by university students.

II. Methodology

A. Data Collection

Eighteen graduate students from Taiwan's National Chiao Tung University (NCTU) participated in this study from March 19, 2015, to June 17, 2015 [4]. While in class, students participating in this study underwent the following routine, as shown in Fig. 1: DASS-21, Resting Session A, a 60-minute stressful session, Resting Session B, and another DASS-21.

Fig. 1: Data collection in classrooms.

Before class, students would take the Depression, Anxiety, and Stress Scales - 21 Items (DASS-21) assessment. The DASS comprises three self-reported scales to measure a subject's depression, anxiety, and stress levels [5]. While the original DASS is a 42-item questionnaire, a modified, 21-item questionnaire was given to the students [6].

Immediately after completing the DASS-21, five minutes of eye-open resting-state EEG were collected. Students then had sixty minutes of EEG data recorded during the stressful sessions. The stressful sessions referred to students taking exams/quizzes or were asked questions by the teachers [4]. Following the stressful session, students would record another five minutes of eye-open resting-state EEG and complete another DASS-21 assessment. The first and last resting-state EEG collecting sessions were called Resting Sessions A and B, respectively.

B. EEG Data Processing

We used MATLAB's EEGLAB toolbox to pre-process the EEG data. EEGLAB was used to calculate and plot power spectral densities (PSDs) across different regions. The changes in power spectral densities between Resting Sessions A and B were then calculated and used as EEG features to train machine learning models.

The data labels used for machine learning analysis were derived from the subjective DASS-21 stress scores reported at the beginning and end of the experiment. We differentiated between students whose stress decreased, increased, and didn't change after the stressful session. The total dataset had seven samples with reduced stress, five with increased stress, and fourteen with no change in stress.

C. Feature Selection and Processing Pipeline

This study aimed to validate the efficacy of asymmetric features as a stress marker. We define EEG asymmetry as the spectral difference between the left and right hemispheres of the brain. EEG asymmetry index was computed using the logarithmic difference of the resting-state EEG signals between a pair of EEG channels, as shown in (1). Here, P_{left} represents the channel power in the left hemisphere, and P_{right} represents the corresponding channel power in the right hemisphere.

$$AsymmetryIndex = ln(\frac{P_{left}}{P_{right}}) \quad (1)$$

This study used EEG asymmetry in eight pairs of channels for classification: FP1 and FP2, F3 and F4, FC3 and FC4, FT7 and FT8, C3 and C4, CP3 and CP4, P3 and P4, and TP7 and TP8. We investigated these channel pairings in the theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (30-40 Hz) frequency bands.

D. Statistical Testing on EEG Asymmetry indexes

Across the different frequency bands, we separated the EEG asymmetry indexes based on the increased and decreased stress groups. We then performed the Mann-Whitney U test on the separated data for each channel pairing.

E. Initial Model Selection

It is imperative to select a machine-learning classifier that can perform well across various EEG channels and frequency bands. Based on the statistical testing results shown in Fig. 3, EEG asymmetry indexes in the alpha and beta bands exhibited statistical differences between the increase and decrease stress groups. Hence we used the asymmetry indices in these bands as the EEG features for the initial model selection. Several multi-class classification models (see Fig. 4) were trained on these asymmetry indices to compare their balanced accuracy and loss. We performed three-fold cross-validation, splitting the data into divisions of 70-20-10, corresponding to training, validation, and testing. Specifically, each model was first trained and tested using the alpha asymmetry indexes for each of the eight EEG pairings separately, followed by the same process for the beta asymmetry indexes. We then took the average of the balanced accuracy and loss for each model.

F. Classification of Samples With Increased and Decreased Stress Levels

As stated earlier, our dataset comprises 7 samples with reduced stress, 5 with increased stress, and 14 with no change in stress. We define this dataset as the baseline data. To address the issue of unbalanced class assignments, we utilized the Synthetic Minority Oversampling Technique (SMOTE) to construct our training data. SMOTE generates synthetic samples for the minority class until the number of samples in both the majority and minority classes are equal [7]. In our study, SMOTE was applied so that the decreased and increased stress groups had 14 samples. This artificially over-sampled dataset is referred to as the SMOTE data. Table I provides a visual reference to the number of samples in each class.

TABLE I: Sample counts in the baseline & SMOTE datasets.

Changes in DASS-21	Class	Baseline	SMOTE
Stress scores increased	Increase	5	14
Stress scores decreased	Decrease	7	14
No change in scores	No change	14	14
Total		26	42

The selected classification algorithm was applied to all datasets after using SMOTE. We tested the models using three-fold cross-validation and leave-one-session-out (LOSO) cross-validation. Finally, we calculated each dataset's loss and balanced accuracy with both validation methods.

III. Results

A. Visual Inspection of PSDs Over the Scalp

Fig. 2 illustrates the spectral amplitudes of the scalp's resting-state EEG while students had increased and decreased stress levels. There are discernible changes between the two conditions. Notably, in the theta band, the spectral amplitude in the frontal region was lower in the group with decreased stress. In the right parietal region, the alpha band exhibited a reduced spectral amplitude in the increased stress group. The subjects in the group with stress reduction do not appear to have this alpha depression. The beta power in the frontal and central regions seems lower in the group with increased stress. In contrast, the group with decreased stress had less power in the temporal region. The gamma band showed less power in the right parietal region for the increased-stress group compared to the reduced-stress group.

B. Statistical Testing Results

Fig. 3 shows the results of the statistical testing of asymmetric pairing in the different frequency bands. A p-value of 0.05 was used. Among the frequency bands, we observed statistical significance in the alpha band at F3/F4 and in the beta band at FP1/FP2.

C. Initial Model Selection Results

Fig. 4 compares balanced accuracy and loss among various machine learning classifiers. Due to its maximum balanced accuracy and least validation loss, the Random Forest Classifier was the ideal choice for future investigations.

D. Performance of Stress Classification

Tables II, III, IV, and V report the balanced accuracy for the theta, alpha, beta, and gamma banded asymmetry pairings, respectively. We performed three-fold cross-validation on the baseline and SMOTE results. Additionally, we performed LOSO cross-validation on the SMOTE results.

TABLE II: Accuracy achieved from theta asymmetry.

Channel 1	Channel 2	Freq Bands	Balanced Accuracy		
			Baseline	SMOTE	LOSO
FP1	FP2	4-7 Hz	0.27	0.40	0.61
F3	F4	4-7 Hz	0.24	0.66	0.69
FC3	FC4	4-7 Hz	0.25	0.58	0.61
FT7	FT8	4-7 Hz	0.50	0.65	0.69
C3	C4	4-7 Hz	0.21	0.59	0.66
CP3	CP4	4-7 Hz	0.39	0.51	0.64
TP7	TP8	4-7 Hz	0.20	0.39	0.41
P3	P4	4-7 Hz	0.28	0.40	0.51

It can be seen that in Table II, pairings F3/F4 and FT7/FT8 in the theta band recorded the highest balanced accuracy using LOSO analysis. In Table III, pairing F3/F4 in the alpha band recorded the highest balanced accuracy using 3-fold and LOSO cross-validation. In Table IV, pairing FP1/FP2 in the

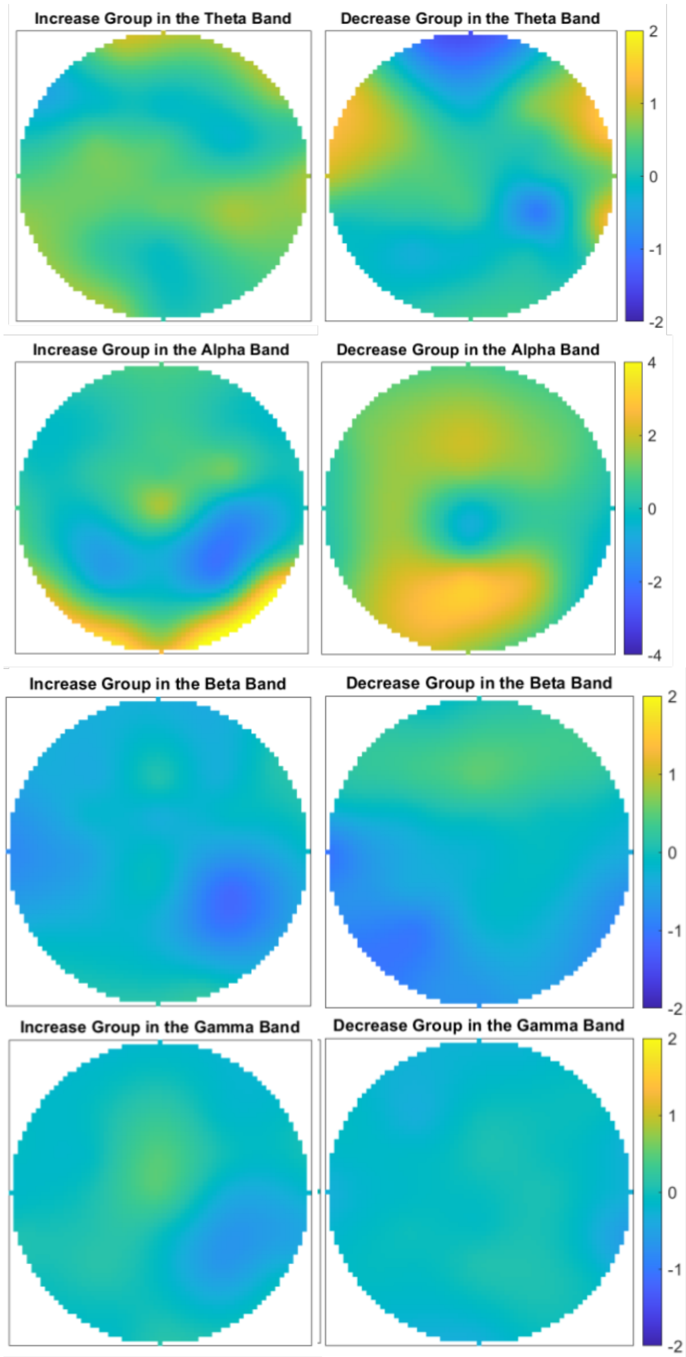

Fig. 2: Topoplots of the spectral amplitudes of the resting-state EEG in four frequency bands when subjects experienced increased (left) vs. decreased (right) stress.

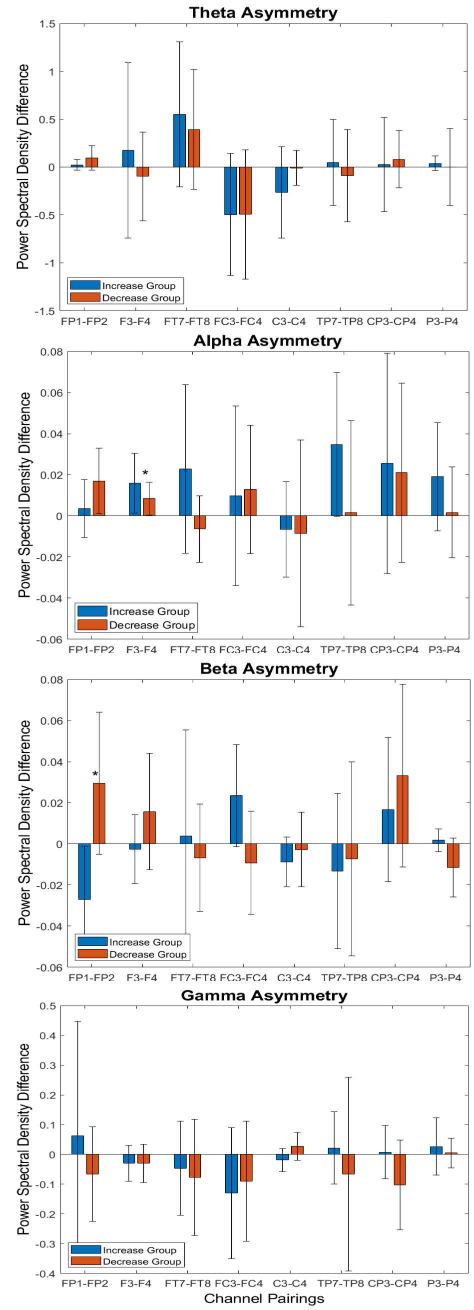

Fig. 3: Statistical testing results of the EEG asymmetry indexes between the increased- and decreased-stress conditions. The significance level was set at $p \leq 0.05$.

TABLE III: Accuracy achieved from alpha asymmetry.

Channel 1	Channel 2	Freq Bands	Balanced Accuracy		
			Baseline	SMOTE	LOSO
FP1	FP2	8-12 Hz	0.44	0.61	0.64
F3	F4	8-12 Hz	0.60	0.79	0.79
FC3	FC4	8-12 Hz	0.13	0.69	0.74
FT7	FT8	8-12 Hz	0.22	0.67	0.64
C3	C4	8-12 Hz	0.26	0.74	0.64
CP3	CP4	8-12 Hz	0.29	0.65	0.74
TP7	TP8	8-12 Hz	0.26	0.69	0.77
P3	P4	8-12 Hz	0.32	0.56	0.72

TABLE IV: Accuracy achieved from beta asymmetry.

Channel 1	Channel 2	Freq Bands	Balanced Accuracy		
			Baseline	SMOTE	LOSO
FP1	FP2	13-30 Hz	0.31	0.71	0.82
F3	F4	13-30 Hz	0.44	0.66	0.72
FC3	FC4	13-30 Hz	0.29	0.60	0.78
FT7	FT8	13-30 Hz	0.30	0.54	0.72
C3	C4	13-30 Hz	0.31	0.64	0.69
CP3	CP4	13-30 Hz	0.36	0.60	0.59
TP7	TP8	13-30 Hz	0.29	0.58	0.72
P3	P4	13-30 Hz	0.27	0.48	0.44

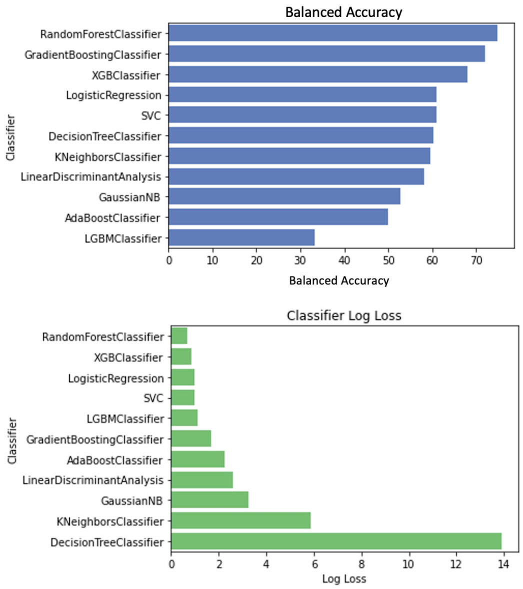

Fig. 4: A comparison of balanced accuracy and loss among various machine learning classifiers.

TABLE V: Accuracy achieved from gamma asymmetry.

Channel 1	Channel 2	Freq Bands	Balanced Accuracy		
			Baseline	SMOTE	LOSO
FP1	FP2	30-40 Hz	0.33	0.60	0.69
F3	F4	30-40 Hz	0.43	0.63	0.64
FC3	FC4	30-40 Hz	0.49	0.43	0.69
FT7	FT8	30-40 Hz	0.47	0.27	0.74
C3	C4	30-40 Hz	0.24	0.56	0.62
CP3	CP4	30-40 Hz	0.20	0.46	0.74
TP7	TP8	30-40 Hz	0.31	0.58	0.69
P3	P4	30-40 Hz	0.15	0.49	0.67

beta band recorded the highest balanced accuracy with LOSO and SMOTE analysis. Finally, in Table V, pairing CP3/CP4 and FT7/FT8 in the gamma band recorded the highest balanced accuracy with LOSO validation. However, it's worth mentioning that SMOTE led to improved balanced accuracy in both cross-validation methods across all frequency bands.

The high classification accuracy achieved through the alpha asymmetry at F3/F4 and beta asymmetry at FP1/FP2 suggests that merging these features is a logical step toward developing a stress monitoring system. This combination led to a balanced accuracy of **85.71%** when tested using leave-one-subject-out cross-validation.

IV. Discussion

Study results showed the feasibility of accurately classifying alterations in subjective stress using EEG channels through a one-size-fits-all machine learning algorithm. Specifically, the channel pairing F3/F4 recorded the highest balanced accuracy of 79% in the alpha frequency band when validated using 3-fold cross-validation and LOSO. Meanwhile, the channel pairing FP1/FP2 in the beta band showed the highest balanced accuracy of 82% when validated with LOSO. The efficacy of these channel pairings in their respective frequency bands is further supported by the results shown in Fig. 3, which reveal the ability to statistically distinguish between increased and decreased-stress sessions, even without machine learning classification. The theta and gamma bands showed less effectiveness compared to the alpha and beta bands. Additionally, the balanced accuracy significantly improved in both cross-validation cases when the dataset was artificially increased using SMOTE. This outcome was anticipated as SMOTE has been demonstrated to enhance smaller datasets effectively [7]. However, it is noteworthy that this study showed accurate and non-invasive stress level estimation is possible using EEG asymmetry recorded from as few as two scalp sites.

While this study shows promising results in classifying self-reported stress, there is room for improvement in the methods used. Specifically, one possibility would be to optimize feature selection based on spatial and temporal EEG features. For instance, Fig. 2 shows distinct regions of lower and higher power when the participants experienced increased versus decreased stress. Investigating a feature space based on channels exhibiting spectral changes could be a valuable approach. Furthermore, it is possible that a one-size-fits-all machine learning algorithm is not the most effective approach for stress classification. For example, different machine learning classifiers may better differentiate stress changes in distinct brain regions.

V. Conclusion

This study details the use of the Random Forest algorithm and SMOTE in stress monitoring by applying them to EEG asymmetry-based channel pairings from students experiencing stress changes in a classroom setting. Study results suggest that alpha asymmetry at F3/F4 and beta asymmetry at FP1/FP2 could serve as promising biomarkers for stress detection. Combining alpha power at F3/F4 and beta power at FP1/FP2 results in a balanced classification accuracy of 85.71% in LOSO cross-validation.

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