Accurate Mental Stress Detection Using Sequential Backward Selection and Adaptive Synthetic Methods

Journal:	*IEEE Transactions on Neural Systems & Rehabilitation Engineering*
Manuscript ID	TNSRE-2024-00123
Manuscript Type:	Paper
Date Submitted by the Author:	01-Feb-2024
Complete List of Authors:	Tseng, Hui-Chun; National Yang Ming Chiao Tung University Department of Computer Science Tai, Kuang-Yi; National Yang Ming Chiao Tung University Department of Computer Science Ma, Yu-Zheng; National Yang Ming Chiao Tung University Department of Computer Science Van, Lan-Da; National Yang Ming Chiao Tung University Department of Computer Science Ko, Li-Wei; National Yang Ming Chiao Tung University Institute of Bioinformatics and Systems Biology Jung, Tzyy-Ping; University of California San Diego Department of Bioengineering; National Yang Ming Chiao Tung University; University of California San Diego Institute for Neural Computation
TIPS (OLD):	
Keywords:	Adaptive synthetic (ADASYN), electroencephalogram (EEG), leave-one-out (LOO), sequential backward selection (SBS), stress detection

Accurate Mental Stress Detection Using Sequential Backward Selection and Adaptive Synthetic Methods

Hui-Chun Tseng, Kuang-Yi Tai, Yu-Zheng Ma, Lan-Da Van*, Li-Wei Ko and Tzyy-Ping Jung*, *Fellow, IEEE*

***Abstract*—The daily experience of mental stress profoundly influences our health and work performance while concurrently triggering alterations in brain electrical activity. Electroencephalogram (EEG) is a widely adopted method for assessing cognitive and affective states. This study delves into the EEG correlates of stress and the potential use of resting EEG in evaluating stress levels. Over 13 weeks, our longitudinal study focuses on the real-life experiences of college students, collecting data from each of the 18 participants across multiple days in classroom settings. To tackle the complexity arising from the multitude of EEG features and the imbalance in data samples across stress levels, we use the sequential backward selection (SBS) method for feature selection and the adaptive synthetic (ADASYN) sampling algorithm for imbalanced data. Our findings unveil that delta and theta features account for approximately 50% of the selected features through the SBS process. In leave-one-out (LOO) cross-validation, the combination of band power and pair-wise coherence (COH) achieves a maximum balanced accuracy of 94.8% in stress-level detection for the above daily stress dataset. Notably, using ADASYN and borderline synthesized minority over-sampling technique (borderline-SMOTE) methods enhances model accuracy compared to the traditional SMOTE approach. These results provide valuable insights into using EEG signals for assessing stress levels in real-life scenarios, shedding light on potential strategies for managing stress more effectively.**

***Index Terms*—Adaptive synthetic (ADASYN), electroencephalogram (EEG), leave-one-out (LOO), sequential backward selection (SBS), synthesized minority over-sampling technique (SMOTE), stress detection.**

Manuscript received Jan. 30, 2024. This work was supported in part by the Ministry of Science and Technology Grant NSTC 112-2221-E-A49-15, NSTC 112-2321-B-A49-012 from Taiwan and a grant (NCS-1734883) from the NSF of USA. The Institutional Review Board of National Yang Ming Chiao Tung University (NYCU) approved this study (IRB# NCTU-REC-103-025). (Corresponding authors: Lan-Da Van; Tzyy-Ping Jung.)

Hui-Chun Tseng, Kuang-Yi Tai, and Yu-Zheng Ma are with the Department of Computer Science, National Yang Ming Chiao Tung University, Taiwan. (E-mail: huichuntseng.c@nycu.edu.tw)

Lan-Da Van is with the Department of Computer Science, National Yang Ming Chiao Tung University, Taiwan. (E-mail: ldvan@cs.nycu.edu.tw)

Li-Wei Ko is with the Institute for Bioinformatics and Systems Biology, National Chiao Tung University, Hsihncu 30010, Taiwan. (e-mail: lwko@nycu.edu.tw).

Tzyy-Ping Jung is with the Institute for Neural Computation, Department of Bioengineering, University of California San Diego, La Jolla, CA 92093 USA and National Yang Ming Chiao Tung University, Taiwan. (E-mail: tpjung@ucsd.edu)

I. INTRODUCTION

THE rapid pace of modern life and the growing daily stressors have heightened interest in understanding the impact of stress on the human brain. As a result, the non-invasive detection of stress has gained popularity recently [1]. EEG signals, because of their non-invasive, straightforward, and cost-effective nature, are an invaluable source of information encompassing cognition, emotions, mental states, spirit, and psychological activities [2]. Researchers often employ EEG signals in their investigations of real-life stress. EEG signals are typically categorized into distinct frequency bands, including delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (14-30 Hz), and gamma (30-50 Hz) [3]. Several studies have shown the use of power spectral density (PSD) in measuring stress levels. For instance, the study in [4] showed reduced alpha power with increasing stress levels during a mental arithmetic task. Komarov *et al.* [5] found that Theta and low-alpha PSD increase significantly with anxiety and stress levels. Moreover, various EEG features, including asymmetry, coherence, mutual information, and entropy between pairs of channels, offer valuable insights into cognitive and affective states. For instance, Wu *et al.* [6] notably reported the efficacy of EEG channel pair coherence in detecting major depressive disorder (MDD).

Despite the wealth of informative features available for stress detection, including asymmetry, PSD, and entropy, the diverse range of these features give rise to a common challenge known as the "curse of dimensionality." To mitigate this issue, researchers have employed various techniques to reduce feature space, encompassing both feature extraction and feature selection methods. Giannakakis *et al.* [7] used the sequential forward selection (SFS) feature-selection method to identify 20 critical features associated with the stress/anxiety state from a pool of 237 features, such as PSD, asymmetry index, and Hjorth. Yang *et al.* [8] used a hybrid feature selection method (ST-SBSSVM) to reduce dimensionality, processing ten types of features, including both linear and nonlinear features. This approach resulted in a model capable of efficiently handling high-dimensional features, demonstrating effective accuracy of DEAP and SEED datasets. Günaydin *et al.* [9] ocused on detecting the driver's stress state using 42 statistical features from EEG and EDA signals. They enhanced the model's accuracy through the SFS feature selection method. Additionally, they addressed imbalanced data concerns by applying the SMOTE method to prevent

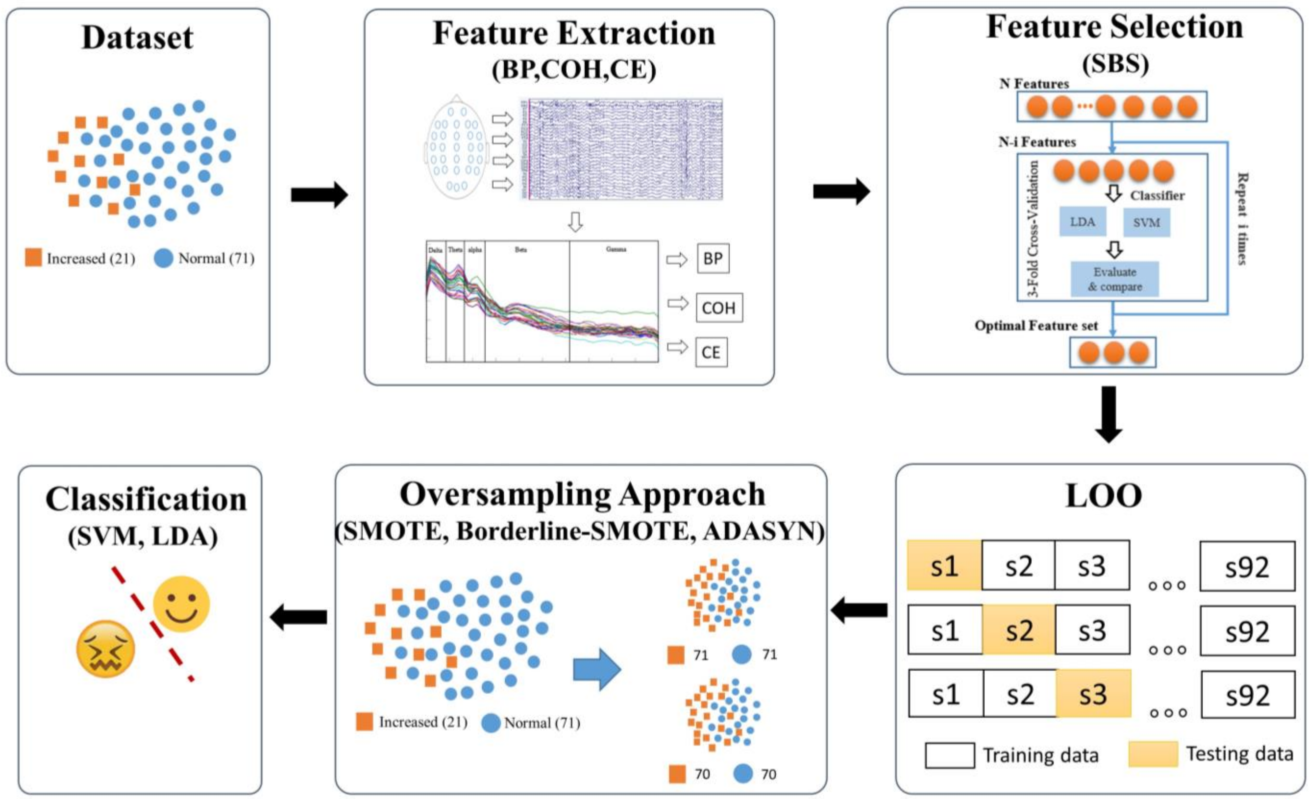

Fig. 1. Method overview. First, this pipeline performed feature extraction and selected the most appropriate number of features using the SBS feature selection approach. Regarding training, the dataflow implemented LOO cross-validation and the SMOTE algorithm. Finally, classify normal/ increased stress and denote the results in balanced accuracy using LDA and SVM.

biased models. However, as pointed out by [10], there remains room for improvement in the stress detection method, particularly concerning feature extraction and selection. This study uses a feature-selection approach in combination with multiple efficient classifiers to detect stress levels. Additionally, we employed over-sampling techniques to address the imbalanced data samples across different stress levels during model training to improve classification performance.

Contributions of this study include: (1) We explored band power, coherence, and conditional entropy associated with five frequency bands to extract a comprehensive EEG feature set. (2) We used the SBS method to effectively reduce the dimensionality of EEG features and select the most relevant ones. (3) The LOO cross-validation was applied to achieve an impartial performance comparison and prevent over-fitting. (4) We used the ADASYN sampling method to address imbalanced data. (5) Integrating these methods yields new findings and improves stress detection accuracy to 94.8% for the daily stress dataset.

II. Proposed Method

A. Dataset

This dataset comprises the EEG signals and self-reported scores of depression, anxiety, and stress based on a 21-item version (DASS-21) [11], from a group of 18 participants, ages 23 to 27 years. The Institutional Review Board of National Yang Ming Chiao Tung University (NYCU) approved this study (IRB# NCTU-REC-103-025). Data collection occurred between March 19, 2015, and June 17, 2015 [5]. We recorded the EEG signals from 30 electrodes placed according to the 10-20 system, and we sampled these signals at 1000Hz. The participants in this study attended the class at the same time every week, and we collected the EEG signals using the following steps: (1) Participants (students) completed the DASS 21 survey to assess their psychological well-being before recording. (2) Record the resting-state EEG signals with the eyes open for five minutes before the class. (3) Attend the 60-minute stressful class and record the EEG data. (4) We recorded another five-minute resting state EEG signals after the class. The primary aim of this study was to explore the relationship between long-term stress and EEG signals. To do so, we analyzed the five-minute resting state EEG signals recorded before each class in 92 sessions. Based on the feedback obtained through the DASS-21 scale, we categorized the sessions into two groups: one with increased stress levels (21 sessions) and another with normal stress levels (71 sessions). This categorization allowed us to investigate the connections between stress and EEG patterns.

B. EEG Data Processing Pipeline

Fig. 1 summarizes the architectural framework used in this study. To ensure data quality, we employed EEGLAB's ICA algorithm [10], [12] to eliminate eye-movement artifacts and implemented band-pass filtering, restricting the signal's frequency range from 1Hz to 50Hz to mitigate high-frequency noise. Our aim in classifying stress states involved the extraction of key features, specifically band power (BP), coherence (COH), and conditional entropy (CE). This endeavor resulted in a rather substantial number of features, totaling 4500. To streamline our analysis, we adopted the SBS feature selection method to identify the most pertinent features for stress detection.

Before model training, we took additional steps to ensure the integrity of our dataset. Those steps included employing a data-independent approach and using the SMOTE algorithm to balance the dataset, which was essential to prevent class imbalance issues. In the final stage of our analysis, we used two well-established classifiers, linear discriminant analysis (LDA) and support vector machine (SVM), to characterize and classify the stress state. These classifiers serve as robust tools for our stress detection task.

C. Feature Extraction

1) Band power

The PSD is a widely employed method in signal processing that reveals how power is distributed in a time-series signal. Several EEG studies have shown the importance of PSD features in stress detection [5],[10]. Stress detection typically entails the use of standard frequency band ranges, including delta, theta, alpha, beta, and gamma [10]. In this study, we computed the PSD for each electrode using the EEGLab Toolbox. We converted the PSD feature estimations into decibels (dB) to facilitate the observation of amplitude variations and differences among frequency bands. Following the previously mentioned frequency band ranges, we calculated the band power. Consequently, the EEG signal provided 150 PSD features, which results from multiplying five frequency bands by 30 channels.

2) Coherence

Coherence evaluates the similarity between two data sequences and is valuable for examining the relationships between different channels in EEG analysis. Pair-wise coherence calculates this by using the cross-spectrum and power spectrum of the two data sequences. The COH for a specific frequency band in each pair of electrodes can be expressed as:

$$COH_{ij}(f) = \frac{|P_{ij}(f)|^2}{P_{ii}P_{jj}(f)} \tag{1}$$

Where P_{ii} and P_{jj} are the PSD values of channels i and j, and P_{ij} is the cross-spectral density values of channels i and j. $i=1,\ldots,30,\ j=1,\ldots,30$. The length of the window is 2s. We extracted the EEG signals' correlation features for each electrode pair in different frequency bands. The COH features comprised 2,175 features, which resulted from multiplying five frequency bands by 435 electrode pairs.

3) Conditional entropy

The conditional entropy of I given J, denoted by H(I|J), is calculated as [13]:

$$\begin{aligned} \mathrm{H}(I|J) &= \sum_{j=J} p(j)H(I \mid J=j) \\ &= \sum_{i\in I, j\in J} p(i,j)\log\frac{p(i)}{p(i,j)} \end{aligned} \tag{2}$$

Eq. (2) presents a measure of the remaining uncertainty about the random variable I when we have information about the value of J. In this study, we utilized the condentropy function developed by Peng, implemented in C++ and integrated into MATLAB [14]. We derived 2,175 CE features, which resulted from the multiplication of data from five frequency bands by 435 electrode pairs.

D. Feature Selection

As demonstrated earlier, we have derived a substantial number of features, totaling 4,500. To address the need for dimensionality reduction, researchers often categorize techniques into feature extraction and feature selection methods [15]. Feature extraction has an advantage in that the resulting feature sets are generally smaller than those obtained through feature selection. However, a drawback is the lack of physical meaning in these new feature sets. As a result, their interpretability and reliability in medical applications are relatively limited [16].

For instance, features lacking physical meaning may exhibit inconsistencies across different datasets, making applying to new cases challenging. Feature selection represents another approach to dimensionality reduction. It encompasses three common types: filters, embedding, and wrapper methods. Most of the time, wrapper methods outperform filtering techniques as they consider feature interactions [17]. This study used SBS [18] to choose an appropriate feature subset from a large feature set. The SBS algorithm involves a three-step process. In the first step, it creates all feature subsets with N-1 dimensions. We then used these subsets in the second step to train machine learning models and evaluate their performance. The third step involves removing the feature with the poorest performance. This iterative process continues until reaching the desired target number of feature dimensions or when N equals 1, leading to the loop's termination.

E. Model Evaluation

In this study, our imbalanced dataset comprised 71 instances in the normal-stress class and only 21 instances in the evaluated-stress class. Imbalanced data leads classifiers into incorrect detections of minority classes because of the limited number of instances available for training the model [19]. To address this issue, we used SMOTE, an over-sampling approach, to generate synthetic data for the minority class. We adopted the LOO cross-validation method, which is suitable for small datasets and helps mitigate over-fitting [20].

When employing the SMOTE and LOO techniques, two scenarios may arise. If the test set comprises increased data, SMOTE generates synthetic increased-stress data instances to match the 71 instances. In contrast, if the test set contains normal-stress data, SMOTE generates synthetic increased data instances to reach 70 instances. Ultimately, we evaluated the model's accuracy using balanced accuracy (BA) as an

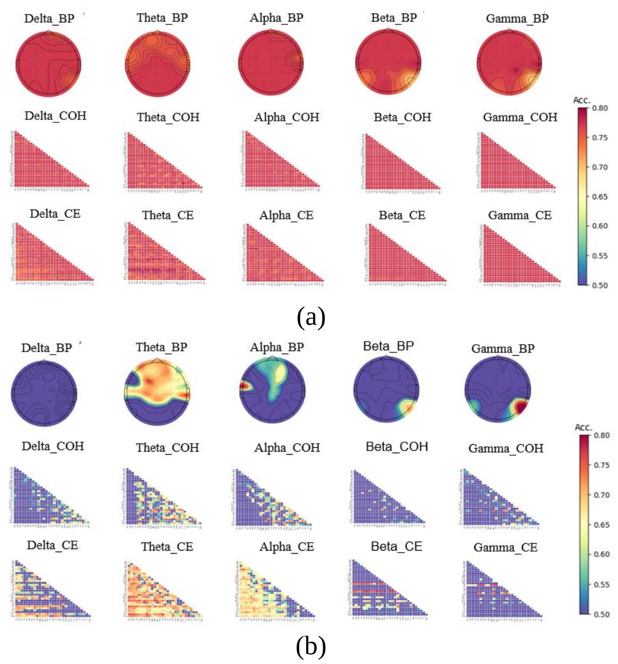

Fig. 2. The topoplots display the classification accuracy of band power features by each electrode. The second and third layers show each pair's classification accuracy of coherence/conditional entropy features. (a) Classification accuracy of the LDA classifier. (b) Classification accuracy of the SVM classifier.

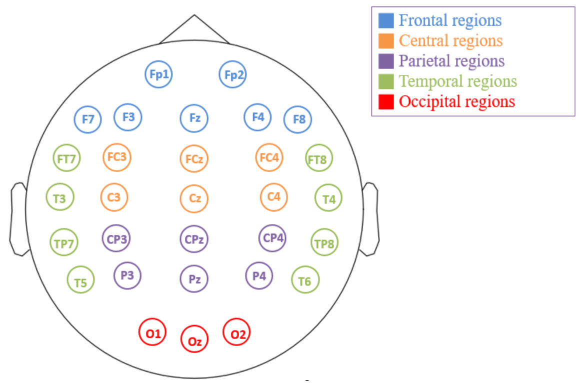

Fig. 3. Electrode layout. Our EEG recording follows the International 10–20 system of electrode placement on the scalp. This study split the entire scalp region into five sections —frontal (blue), central (orange), parietal (purple), temporal (green), and occipital (red).

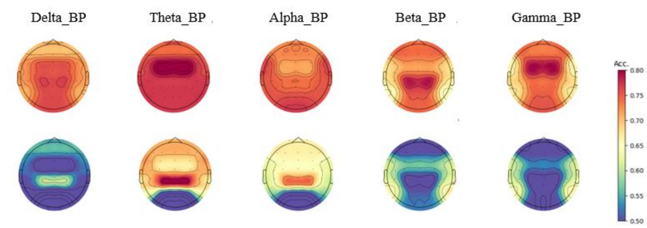

Fig. 4. With LDA (upper) and SVM classifier (bottom), the topoplots display the classification accuracy of features by each brain area.

assessment metric. Given the dataset's imbalance, BA offers a fairer evaluation by considering the significance of each class [21]. We calculate the balanced accuracy:

$$Balanced\ accuracy = \frac{1}{2}\left(\frac{TP}{P} + \frac{TN}{N}\right) \tag{3}$$

III. Results

A. Comparison of Features before Feature Selection

In this section, we compared classification accuracy for features extracted from various scalp regions and electrodes using LDA and SVM classifiers. We applied a five-fold cross-validation for accuracy assessment. Fig. 2 illustrates the classification accuracy across different electrodes using BP, COH, and CE features. Each feature type encompasses delta, alpha, beta, theta, and gamma (e.g., Delta_BP_PF1, Beta_COH_PF1_PF2). In Fig. 2(a) and 2(b), we employed LDA and SVM separately to classify increased and normal stress levels. Notably, we observed a significant difference in classification accuracy between LDA and SVM. LDA achieved an average accuracy of 76.85%, while SVM averaged 42.25%. Regarding BP, SVM exhibited approximately 17.51% higher accuracy in the Theta band than in other frequency bands. For COH and CE, there were 435 feature pairs. In the SVM results, Theta, Alpha, and Delta displayed an advantage of roughly 19.03% over other frequency bands.

Fig. 3 presents the electrode-to-scalp region mapping, which includes frontal, central, parietal, temporal, and occipital regions [6]. In this study, we leveraged grouped regional features within each band to distinguish between increased and normal stress levels. Fig. 4 portrays the classification accuracy of different brain regions across various frequency bands. Compared to results from other frequency bands in the LDA classifier, the Theta band stands out with the highest accuracy at 77.34%. Similarly, SVM also showed superior performance in the Theta band, achieving an accuracy of 67.64%.

B. SBS Result

This section used the SBS feature selection method [18] to identify the most significant features for stress detection. We combined the previously mentioned features into three sets: BP, BP+COH, and BP+CE, using 150, 2325, and 2325 features, respectively. The SBS method integrated LDA and SVM classifiers to identify the best subset features. It used three-fold cross-validation to avoid over-fitting and ensure the usefulness of the selected features.

Fig. 5 visually presents the findings, with the x-axis indicating the number of features chosen by the SBS method. Given that the optimal number of features for all three combinations in LDA and SVM remained below 150, we exclusively displayed accuracy curves for feature counts within the range of [1, 150] in Fig. 5 to provide a clearer perspective. Additionally, when the maximum accuracy is equivalent, we prefer to choose the combination with the smallest total number of features. The pie charts in Fig. 5 show the distribution of the selected features by SBS for each combination. In Fig. 5(a), LDA and SVM selected 22 and 24 features in BP combination at the highest accuracy, respectively. Notably, delta features in the pie chart constituted the most substantial portion, accounting for 32% and 46%, followed by Theta at 27% and 17%.

In Fig 5(b), within the BP+COH combination, LDA and SVM chose 100 and 18 features, respectively, at the

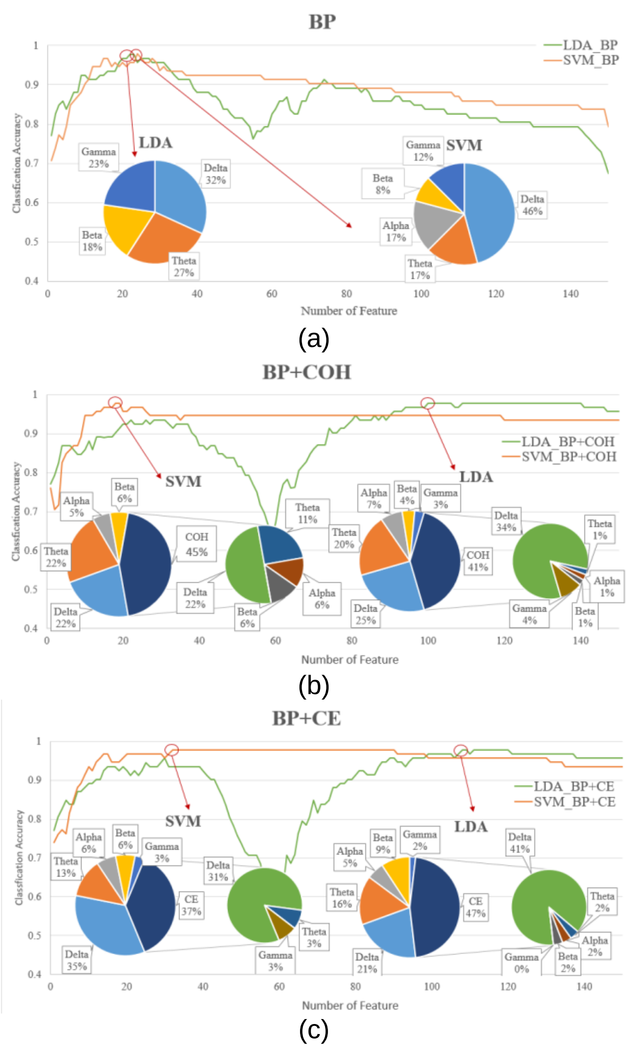

Fig. 5. Classification accuracy over different numbers of features dropped via the SBS algorithm: (a) BP features, (b) BP +COH features, and (c) BP+CE features. The pie chart represents the proportion of the selected features by SBS for the SVM or LDA classifier.

highest accuracy level. Concerning the delta and theta features from the BP part, they represented 45% and 44% in both LDA and SVM classifiers, respectively. Among the COH features (depicted in the smaller pie chart adjacent to the main one), delta features had the highest shares at 34% and 22%. Fig. 5(c) shows that within the BP+CE combination, LDA and SVM selected 108 and 32 features at the highest resolution. In LDA, the primary contributors were Delta_BP (21%), Delta_CE (19%), and Theta_BP (16%), while in SVM, the leading contributors were Delta_BP (35%), Theta_BP (13%), and Delta_CE (11%). To summarize, delta and theta features played a significant role in these three combinations, which are pivotal for distinguishing between normal and heightened stress levels.

Table 1 presents the balanced accuracy results achieved with various combinations of LDA and SVM classifiers using LOO cross-validation. BP exhibits similar balanced accuracy for both LDA and SVM. However, after applying the SMOTE technique, LDA slightly surpasses SVM in performance. Furthermore, in the other two feature combinations, LDA selected nearly five times as many features in the SBS method compared to SVM, with the BP+COH combination using 100 features and the BP+CE combination using 108 features, respectively. Subsequently, following the application of the SMOTE over-sampling method, the SVM classifier attained the highest balanced accuracy in the BP+COH combination, reaching 92.42%.

C. Comparison of Feature Selection Methods

In this section, we compared three different experiments for stress detection: one that includes all features, one with feature selection using SBS, and one with feature selection through PCA. Each experiment applied LOO cross-validation and calculated balanced accuracy. The numbers of features are 150 for BP, 2,325 for BP+COH, and 2,325 for BP+CE. The determination of the number of features for SBS is based on the highest accuracy achieved by different classifiers in the preceding section, and we set n_components to 30 for PCA. We also assessed the classification results of models trained with and without applying the SMOTE method. As shown in Section III.B, the performance of LDA after the SBS feature selection did not meet our expectations. Table 2 presents the results of the LDA classifier, which outperformed SBS, achieving an accuracy of 76.12% in BP+COH combinations when employing the PCA method for feature transformation. Furthermore, within the SVM classifier, the SBS feature selection method outperforms the PCA method across various feature combinations, providing more interpretable results.

D. Comparison of SMOTE Methods

This section examines the impact of several SMOTE over-sampling techniques, including SMOTE, Borderline SMOTE, and ADASYN. Borderline SMOTE, a variation of SMOTE, expands the minority class with new samples near the decision border [22]. ADASYN, on the other hand, automatically generates new samples based on the sample distribution [23]. Each experiment used parameters with k_neighbors=10 and random_state=2. Table 3 illustrates that using ADASYN or Borderline SMOTE enhances model accuracy compared to the conventional SMOTE method. Particularly, applying ADASYN to the SVM approach in the BP+COH combination yielded the highest classification accuracy, reaching 94.8%.

E. Comparison with Previous Research : Selected PSD Features from Fz, FCz, and Cz

Researchers use two primary methods for data collection in current stress detection-related datasets. One method entails using short-term artificial stimuli, such as gaming tasks, to gather EEG signals [7], [9]. The alternative approach avoids relying on external stimulation sources and conducts long-term experiments to acquire EEG signals [10], [24], and our work. Clinical studies showed that chronic stress is a significant factor contributing to the development of stress-related diseases [25].

In Table 4, we compare our work with the most stress detection works in terms of dataset, stimuli, number of subjects, feature extraction method, feature selection method, imbalanced method, best classifier, accuracy and the validation approach. The table highlights the practicality of using PSD and coherence as extraction features for stress classification for daily stress data (i.e., no stimuli). Meanwhile, the SBS

TABLE 1
COMPARE THE LDA AND SVM CLASSIFICATION ACCURACY AMONG DIFFERENT COMBINATIONS.

Combination	BP		BP+COH		BP+CE	
Classifier	LDA	SVM	LDA	SVM	LDA	SVM
Features	22	24	100	18	108	32
w/o SMOTE	89.34%	87.66%	49.87%	**92.42%**	69.25%	81.92%
w/ SMOTE	90.31%	83.17%	49.87%	**92.42%**	69.25%	78.84%

TABLE 2
Compare three feature combinations and the effects of SMOTE on LDA and SVM models, which are for stress detection.

Combinations		ALL Features	SBS	PCA	ALL Features	SBS	PCA
			LDA			SVM	
BP	w/o SMOTE	61.4%	**89.34%**	61.57%	73.91%	**87.66%**	61.27%
	w/ SMOTE	61.4%	**90.31%**	68.54%	72.5%	**83.17%**	73.41%
BP+COH	w/o SMOTE	58.22%	49.87%	**71.8%**	62.01%	**92.42%**	64.08%
	w/ SMOTE	62.54%	49.87%	**76.12%**	69.85%	**92.42%**	66.63%
BP+CE	w/o SMOTE	**71.53%**	69.25%	67.04%	71.53%	**81.92%**	56.3%
	w/ SMOTE	**74.18%**	69.25%	69.68%	70.82%	**78.84%**	69.18%

TABLE 3
The impact of various smote methods.

Combinations	LDA			SVM		
	SMOTE	Borderline SMOTE	ADASYN	SMOTE	Borderline SMOTE	ADASYN
BP	90.31%	89.60%	**91.01%**	83.17%	**91.01%**	84.57%
BP+COH	49.87%	**65.73%**	52.95%	92.42%	90.31%	**94.8%**
BP+CE	**69.25%**	57.18%	68.28%	78.84%	**85.55%**	81.92%

TABLE 4
Comparison with previous research.

Study	Stimuli	#Subjects	Feature extraction method	Feature selection method	Imbalanced method	Best classifier	ACC	Validation Approach
Giannakakis [7](2015)	Music video	18(32)	273 (PSD, COH, BLI, Frontal asymmetry)	SFS	None	None	None	Subject-dependent
GUnaydin [9](2020)	playing a racing game	1	42 (Statistical characteristics)	SFS	None	KNN	70.74%	Subject-dependent
Saeed [24](2020)	Daily Stress (No stimuli)	33	45 (PSD, Differential asymmetry)	t-test	None	SVM	85.20%	Subject-dependent
Chang [10](2022)	Daily Stress (No stimuli)	92	150 (PSD)	None	SMOTE	LDA	79.64% (Balanced accuracy)	Subject -independent
This work	Daily Stress (No stimuli)	92	2325 (PSD,COH,CE)	SBS	ADASYN	SVM	94.8% (Balanced accuracy)	Subject -independent

Note: In the #subjects column, Numbers in brackets mean the original total subjects. BLI: The Brain Load Index.

performs better than SFS when many features exist. Furthermore, we compare our approach and previous research [10] that used PSD features spanning the theta frequency range of 3Hz to 7Hz, encompassing five frequency bins. The prior study and our research employ the same dataset, using LOO cross-validation and the SMOTE techniques for model training. We assess LDA classification results based on balanced accuracy. Table 4 demonstrates that the SBS algorithm selects features that extend beyond just the theta band, encompassing features from various frequency bands and resulting in better classification performance. Using SBS in our work aids in automatically discovering additional facets relevant to stress detection within a vast feature set. To our best knowledge, we are the first one to present the method flow concept in Fig. 1 and Table 4 for stress detection event the presented method with some modifications can be applied to different topics like [8], [26] to search the different scientific findings.

IV. DISCUSSION

The research outcomes highlight the advantages of using the SBS feature selection method, particularly when dealing with an extensive feature set. SBS effectively identifies an optimal subset of features through a 3-fold Cross-Validation approach, thereby mitigating the risk of overfitting. Furthermore, using the ADASYN variation of SMOTE for training and the LOO validation method enhanced the model's accuracy and reliability. To assess the model's performance, we used the balanced accuracy evaluation method. Among the various feature combinations, the SVM classifier achieved the highest balanced accuracy of 94.8% in the BP+COH combination (refer to Table 3). Prior research in stress detection has often regarded the theta band as a significant stress indicator [27], [28]. Fig. 4 presents the results of brain region-based classification, underscoring the heightened sensitivity of the theta band to variations in stress levels. In Section III.B, we

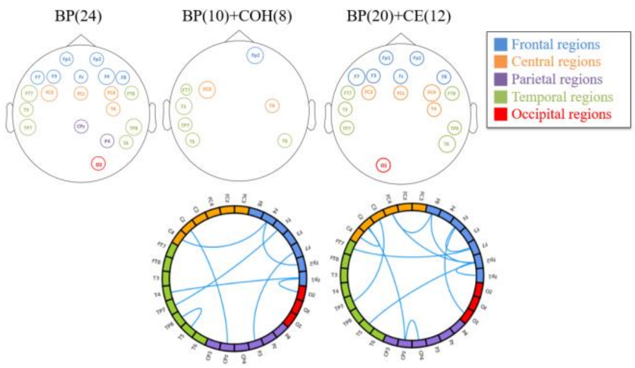

Fig. 6 Distribution of channels with features selected by the SVM-based SBS procedure in three feature combinations (BP, BP+COH, BP+CE). The upper panels illustrate the frequency of each feature within BP, while the lower panels display the chosen electrode pairs from COH and CE.

observed that among the features selected by the SBS method from these three combinations, delta and theta features also played a prominent role.

Regarding stress-related features within various brain regions, it is well-documented that the frontal region significantly influences stress detection [29], [30]. Based on their frequency of selection, the upper panels in Fig. 6 display the BP features chosen by SBS across three feature combinations (BP, BP+COH, and BP+CE). Notably, the BP and BP+CE combinations encompass features from the frontal and temporal regions. In contrast, the lower panels of Fig. 6 showcase the electrode pairs selected by SBS in COH and CE. These electrode pairs, including frontal-frontal, frontal-central, and frontal-temporal regions, are ALL primarily associated with the frontal region, shedding light on the link between the selected features and the frontal region.

Coherence analysis in EEG, used in our stress assessment, offers the advantage of unaffected by amplitude oscillations in various brain regions [3]. This analysis provides a better understanding of the relationship between stress and brain communication [31]. These findings further underscore the enhanced performance of using BP+COH features over BP features alone, resulting in an improvement from 84.57% to 94.8% (refer to Table 3).

While feature selection methods have limitations, they offer interpretability in selecting features and serve as valuable references for scientists investigating stress detection. However, the feature extraction techniques used in this study can be further refined. Several studies have shown the effectiveness of additional EEG features, such as brain asymmetry and mutual information, in stress detection [3]. As a result, future research will focus on exploring and integrating these EEG features to enhance the capabilities of stress detection.

V. Conclusions

The study provides a comprehensive overview of feature selection methods and the application of the ADASYN algorithm in EEG-based stress detection for the daily stress dataset. It explores various frequency bands and features, including BP, COH, and CE. The findings highlight the substantial contributions of delta and theta band features across many feature combinations. Furthermore, all features selected by SBS are linked to the frontal region. Lastly, the classification results conclusively show that the BP+COH combination achieves the highest balanced accuracy of 94.8% in LOO cross-validation.

References

[1] N. Sharma and T. Gedeon, "Objective measures, sensors and computational techniques for stress recognition and classification: A survey," *Computer Methods and Programs in Biomedicine*, vol. 108, no. 3, pp. 1287–1301, Dec. 2012, doi: 10.1016/j.cmpb.2012.07.003.

[2] S. M. Alarcao and M. J. Fonseca, "Emotions Recognition Using EEG Signals: A Survey," *IEEE Trans. Affective Comput.*, vol. 10, no. 3, pp. 374–393, Jul. 2019, doi: 10.1109/TAFFC.2017.2714671.

[3] R. Katmah, F. Al-Shargie, U. Tariq, F. Babiloni, F. Al-Mughairbi, and H. Al-Nashash, "A Review on Mental Stress Assessment Methods Using EEG Signals," *Sensors*, vol. 21, no. 15, p. 5043, Jul. 2021, doi: 10.3390/s21155043.

[4] F. M. Al-shargie, T. B. Tang, N. Badruddin, and M. Kiguchi, "Mental Stress Quantification Using EEG Signals," *Proceedings of the International Conference for Innovation in Biomedical Engineering and Life Sciences*, vol. 56, pp. 15–19, 2016, doi: 10.1007/978-981-10-0266-3_4.

[5] O. Komarov, L.-W. Ko, and T.-P. Jung, "Associations Among Emotional State, Sleep Quality, and Resting-State EEG Spectra: A Longitudinal Study in Graduate Students," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 4, pp. 795–804, Apr. 2020, doi: 10.1109/TNSRE.2020.2972812.

[6] C.-T. Wu *et al.*, "Resting-State EEG Signal for Major Depressive Disorder Detection: A Systematic Validation on a Large and Diverse Dataset," *Biosensors*, vol. 11, no. 12, p. 499, Dec. 2021, doi: 10.3390/bios11120499.

[7] G. Giannakakis, D. Grigoriadis, and M. Tsiknakis, "Detection of stress/anxiety state from EEG features during video watching," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Milan: IEEE, Aug. 2015, pp. 6034–6037. doi: 10.1109/EMBC.2015.7319767.

[8] F. Yang, X. Zhao, W. Jiang, P. Gao, and G. Liu, "Multi-method Fusion of Cross-Subject Emotion Recognition Based on High-Dimensional EEG Features," *Front. Comput. Neurosci.*, vol. 13, p. 53, Aug. 2019, doi: 10.3389/fncom.2019.00053.

[9] O. GUnaydin and R. B. Arslan, "Stress Level Detection Using Physiological Sensors," in *2020 IEEE 20th International Conference on Bioinformatics and Bioengineering (BIBE)*, Cincinnati, OH, USA: IEEE, Oct. 2020, pp. 509–512. doi: 10.1109/BIBE50027.2020.00088.

[10] C.-Y. Chang, "Brain-computer Interfaces for Online Mental Stress Monitoring in the Real World," UC San Diego, 2022. [Online]. Available: ProQuest ID: Chang_ucsd_0033D_22026. Merritt ID: ark:/13030/m53z5kd8. Retrieved from https://escholarship.org/uc/item/7bk415gm

[11] M. M. Antony, P. J. Bieling, B. J. Cox, M. W. Enns, and R. P. Swinson, "Psychometric properties of the 42-item and 21-item versions of the Depression Anxiety Stress Scales in clinical groups and a community sample.," *Psychological Assessment*, vol. 10, no. 2, pp. 176–181, Jun. 1998, doi: 10.1037/1040-3590.10.2.176.

[12] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of Neuroscience Methods*, vol. 134, no. 1, pp. 9–21, Mar. 2004, doi: 10.1016/j.jneumeth.2003.10.009.

[13] S. Keshmiri, "Conditional Entropy: A Potential Digital Marker for Stress," *Entropy*, vol. 23, no. 3, p. 286, Feb. 2021, doi: 10.3390/e23030286.

[14] H. Peng, "Mutual Information computation." Jun. 20, 2023. [Online]. Available: https://www.mathworks.com/matlabcentral/fileexchange/14888-mutual-information-computation

[15] Z. Zhao and H. Liu, *Spectral Feature Selection for Data Mining*, 0 ed. Chapman and Hall/CRC, 2011. doi: 10.1201/b11426.

[16] B. Remeseiro and V. Bolon-Canedo, "A review of feature selection methods in medical applications," *Computers in Biology and Medicine*, vol. 112, p. 103375, Sep. 2019, doi: 10.1016/j.compbiomed.2019.103375.

[17] C. Chen, Y. Tsai, F. Chang, and W. Lin, "Ensemble feature selection in medical datasets: Combining filter, wrapper, and embedded feature

selection results," *Expert Systems*, vol. 37, no. 5, Oct. 2020, doi: 10.1111/exsy.12553.

[18] A. U. Haq, J. Li, M. H. Memon, M. Hunain Memon, J. Khan, and S. M. Marium, "Heart Disease Prediction System Using Model Of Machine Learning and Sequential Backward Selection Algorithm for Features Selection," in *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, Bombay, India: IEEE, Mar. 2019, pp. 1–4. doi: 10.1109/I2CT45611.2019.9033683.

[19] S. N. Syakiylla Sayed Daud, R. Sudirman, and T. Wee Shing, "Safe-level SMOTE method for handling the class imbalanced problem in electroencephalography dataset of adult anxious state," *Biomedical Signal Processing and Control*, vol. 83, p. 104649, May 2023, doi: 10.1016/j.bspc.2023.104649.

[20] H. A. Omar, J. S. Domingos, A. Patra, R. Upton, P. Leeson, and J. A. Noble, "Quantification of cardiac bull's-eye map based on principal strain analysis for myocardial wall motion assessment in stress echocardiography," in *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, Washington, DC: IEEE, Apr. 2018, pp. 1195–1198. doi: 10.1109/ISBI.2018.8363785.

[21] K. H. Brodersen, C. S. Ong, K. E. Stephan, and J. M. Buhmann, "The Balanced Accuracy and Its Posterior Distribution," in *2010 20th International Conference on Pattern Recognition*, Istanbul, Turkey: IEEE, Aug. 2010, pp. 3121–3124. doi: 10.1109/ICPR.2010.764.

[22] H. Han, W.-Y. Wang, and B.-H. Mao, "Borderline-SMOTE: A New Over-Sampling Method in Imbalanced Data Sets Learning," in *Advances in Intelligent Computing*, vol. 3644, D.-S. Huang, X.-P. Zhang, and G.-B. Huang, Eds., in Lecture Notes in Computer Science, vol. 3644. , Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 878–887. doi: 10.1007/11538059_91.

[23] Haibo He, Yang Bai, E. A. Garcia, and Shutao Li, "ADASYN: Adaptive synthetic sampling approach for imbalanced learning," in *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, Hong Kong, China: IEEE, Jun. 2008, pp. 1322–1328. doi: 10.1109/IJCNN.2008.4633969.

[24] S. M. U. Saeed, S. M. Anwar, H. Khalid, M. Majid, and U. Bagci, "EEG Based Classification of Long-Term Stress Using Psychological Labeling," *Sensors*, vol. 20, no. 7, p. 1886, Mar. 2020, doi: 10.3390/s20071886.

[25] D. Oken, "The Specificity of Response to Stressful Stimuli: A Comparison of Two Stressors," *Arch Gen Psychiatry*, vol. 15, no. 6, p. 624, Dec. 1966, doi: 10.1001/archpsyc.1966.01730180064009.

[26] R. Xiong, F. Kong, X. Yang, G. Liu, and W. Wen, "Pattern Recognition of Cognitive Load Using EEG and ECG Signals," *Sensors*, vol. 20, no. 18, p. 5122, Sep. 2020, doi: 10.3390/s20185122.

[27] S. A. Awang, P. M. Pandiyan, S. Yaacob, Y. M. Ali, F. Ramidi, and F. Mat, "Spectral Density Analysis: Theta Wave as Mental Stress Indicator," in *Signal Processing, Image Processing and Pattern Recognition*, vol. 260, T. Kim, H. Adeli, C. Ramos, and B.-H. Kang, Eds., in Communications in Computer and Information Science, vol. 260. , Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 103–112. doi: 10.1007/978-3-642-27183-0_12.

[28] M. M. Sani, H. Norhazman, H. A. Omar, N. Zaini, and S. A. Ghani, "Support vector machine for classification of stress subjects using EEG signals," in *2014 IEEE Conference on Systems, Process and Control (ICSPC 2014)*, Kuala Lumpur, Malaysia: IEEE, Dec. 2014, pp. 127–131. doi: 10.1109/SPC.2014.7086243.

[29] O. Attallah, "An Effective Mental Stress State Detection and Evaluation System Using Minimum Number of Frontal Brain Electrodes," *Diagnostics*, vol. 10, no. 5, p. 292, May 2020, doi: 10.3390/diagnostics10050292.

[30] N. L. Lopez-Duran, R. Nusslock, C. George, and M. Kovacs, "Frontal EEG asymmetry moderates the effects of stressful life events on internalizing symptoms in children at familial risk for depression: EEG asymmetry, life events, and internalizing," *Psychophysiol*, vol. 49, no. 4, pp. 510–521, Apr. 2012, doi: 10.1111/j.1469-8986.2011.01332.x.

[31] P. Fries, "A mechanism for cognitive dynamics: neuronal communication through neuronal coherence," *Trends in Cognitive Sciences*, vol. 9, no. 10, pp. 474–480, Oct. 2005, doi: 10.1016/j.tics.2005.08.011.