Chronic Stress Assessment Based on EEG Signals: An Empirical Method for EEG Feature Importance

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Abstract

Chronic stress is a prolonged and constant feeling of stress that could lead to depression and anxiety. It would be useful to have a self-diagnosing tool to help notify individuals before chronic stress becomes unmanageable. EEG analysis has proven effective as a means of human emotion prediction, but studies linking EEG analysis with and chronic stress are limited. To fill this gap, we recorded rest-state EEG and perceived stress scale (PSS) scores for 55 participants. Five frequency bands (delta, theta, alpha, beta, and gamma) and lateral asymmetry between electrode pairs calculated for the alpha and beta bands are extracted as features from the rest-state EEG. A feature selection procedure was performed using a t-tests and feature importance scores based on five classifiers. A RBF SVM achieved a 10-cv score over 0.9 using eight different combinations of frequency bands, electrodes, and asymmetries, namely, $\boldsymbol{\beta_f}$, F3$_{\boldsymbol{\delta}}$, F4$_{\boldsymbol{\delta}}$, F3$_{\boldsymbol{\beta}}$, P4$_{\boldsymbol{\delta}}$, F3$_{\boldsymbol{\gamma}}$, P4$_{\boldsymbol{\theta}}$, and C3$_{\boldsymbol{\theta}}$. This paper shows that data-driven feature selection for EEG signals can yield accurate chronic stress classifiers.

Keywords: Long-term stress, Chronic stress, Electroencephalography

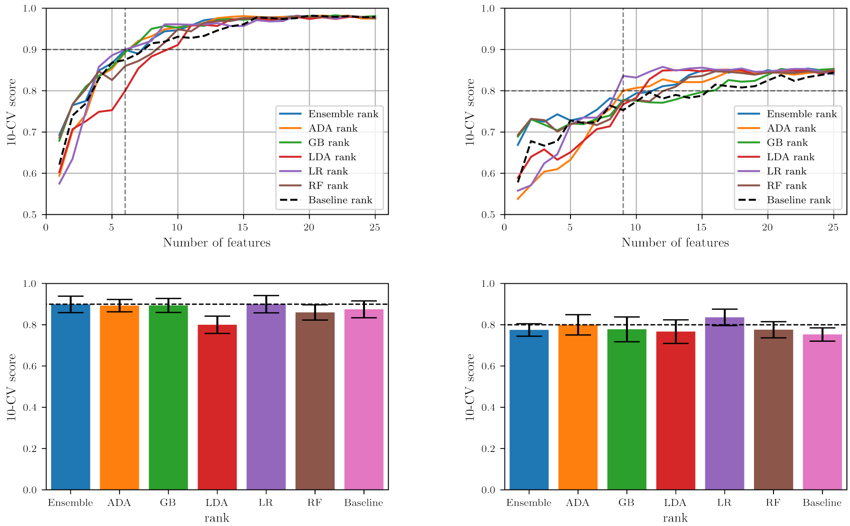
1 Introduction

Stress is an unavoidable life phenomenon that can generate temporary discomfort as well as long-term consequences. Stress can have damaging effects on the mental health of individuals and can be categorized into acute (short-term) and chronic (long-term) occurrences [1]. Acute stress is usually not a health risk, but the persistence of stress for a longer duration becomes chronic [1], which can lead to a state of depression, anxiety, and other possibly life-threatening issues. Chronic stress affects the human body at different levels ranging from skin conditions, eating habits, and inadequate sleeping to decision-making [2–4] and can be a better predictor of depressive symptoms as compared to acute stress [5]. Early detection of chronic stress can therefore reduce the risk of physical and mental illness if the stress is identified and the individual undertakes appropriate stress relief therapies.

Several studies have developed techniques to assess chronic stress using subjective psychological self-report questionnaires such as the Perceived Stress Scale (PSS) [6]. This approach is practical for capturing signs of stress over a long period, but the result could be biased, since participants must reconstruct their feelings from the past, and they may hide their real feelings due to personal circumstances. Some research has found that PSS assessments of chronic stress are generally valid but not perfect [7] so, the PSS alone may not always bring genuine stress to light in self reports. Recently, objective physiological assessments based on bio-markers such as electroencephalography (EEG) signals have emerged as alternative means to detect mental states including acute stress [8, 9]. However, the relationship between chronic stress and EEG signals has not been widely investigated. Although we would ultimately like to predict chronic stress, here we take the somewhat successful less ambitious objective of using EEG to separate less and more stressed individuals according to PSS. Given provocative results, we could then develop a clinical test with appropriate thresholds for chronic level stress. TODO: Admit in the conclusion that more work is needed to make this clinical.

The aim of this study is to identify which EEG features are important contributors to the accuracy of predictive classification for high PSS scores. We performed a study with a total of 55 participants, each of whose rest-state EEG measurements were recorded for ten minutes with eyes closed. The target label for each participant (more stressed or less stressed) was calculated from the statistics of their actual PSS score. An initial 133 features including five EEG frequency bands (delta, theta, alpha, beta, gamma), two custom bands (slow, beta_{low}), and one engineered band ($\text{gamma}_{\text{relative}}$) from 16 electrodes, as well as five lateral asymmetries for alpha and beta bands, were extracted from the recorded EEG signals. We selected the 25 most important features using simple per-feature t-tests. We then ranked the importance of these initial 25 features with six methods. The first five rankings were based on five classifiers' feature importance scores. The five classifiers were Logistic Regression (LR), Linear Discriminant Analysis (LDA), AdaBoost (AB), Gradient Boosting (GB), and Random Forest (RF). The sixth ranking was created by combining the first five rankings using a voting scheme. Finally, the rankings obtained without train-test splits were verified using 10-fold cross validation (10-CV), and t-Distributed Stochastic Neighbor Embedding (t-SNE) was used to visualize the withing-class and between-class similarity of the selected feature vectors for the more stressed and less stressed groups given the selected set of features.

Fig. 1: 10-CV scores for SVM and LR classifiers using different feature important rankings and different numbers of features. Line plots show 10-CV trends as a function of the number of features. Bar plots show 10-CV scores at the overall best number of features, 6 for the SVM and 9 for LR.

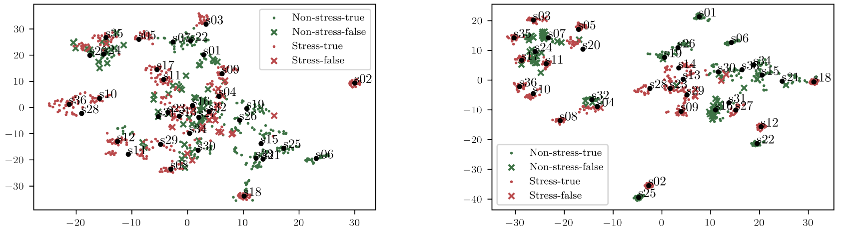


(a) SVM (b) LR

We found that a final SVM with the Radial Basis Function (RBF) kernel achieves a 0.9 10-CV score when using the top six features from $\mathrm{Rank}_{\mathrm{LR}}$ and $\mathrm{Rank}_{\mathrm{Ensemble}}$, as shown in Figure 1a. The top eight features in $\mathrm{Rank}_{\mathrm{Ensemble}}$ are beta_f, $\mathrm{F3}_{\mathrm{delta}}$, $\mathrm{F4}_{\mathrm{delta}}$, $\mathrm{F3}_{\mathrm{beta}}$, $\mathrm{P4}_{\mathrm{delta}}$, $\mathrm{F3}_{\mathrm{gamma}}$, $\mathrm{P4}_{\mathrm{theta}}$, and $\mathrm{C3}_{\mathrm{theta}}$. In addition, t-SNE seems to suggest that the top six $\mathrm{Rank}_{\mathrm{Ensemble}}$ features better reflect the stress grouping than a baseline ranking obtained from the earlier simple individual t-tests, as shown in Figure 2.

This paper implements and assesses several empirical methods for feature selection that combine a t-test initial selection with feature importance scores based on five different classifiers. Our results confirm that with appropriate feature selection, EEG signals acquired from more stressed and less stressed individuals are sufficiently distinctive to classify them according to stress level, and our top eight features agree with conclusion of previous work finding that

Fig. 2: 2D embeddings by t-SNE of the top six features selected by $\mathrm{Rank}_{\mathrm{Baseline}}$ and $\mathrm{Rank}_{\mathrm{Ensemble}}$. Green and red samples indicate less stressed and more stressed groups, respectively, and point shape indicates correct('.') or incorrect('x') classification results with a RBF-SVM. The $\mathrm{Rank}_{\mathrm{Ensemble}}$ features clearly admit a better separated representation than the $\mathrm{Rank}_{\mathrm{Baseline}}$ features.



(a) Baseline (b) Ensemble

the delta and beta frequency bands are the most important frequencies for this task.

2 Related work

Stress is known to cause aberrant reactions in the autonomic nervous system (ANS), including the antagonistic regulation of the sympathetic (SNS) and the parasympathetic (PNS) nervous system [10, 11]. These two systems are associated with stress and relaxation responses, respectively. Changes in the ANS can be detected by EEG signals [12]. In recent years, EEG signals have emerged as a valid modalist for the analysis of mental states including stress [8, 9]. EEG signals can be decomposed into frequency bands [13], each of which is useful for analysis of different brain states [14]. A change of power in beta band is associated with alertness, whereas theta band activity occurs throughout the sleep state, and alpha band activity rises with relaxation [15]. Recent studies have analyzed EEG signals with various signal processing and machine learning methods to detect stress.

Several studies have demonstrated a relationship between stress and EEG signals, and they show that EEG can be used as an input variable for prediction of both short-term and long-term stress. In EEG research, the alpha band is the most commonly used in stress assessment, because it is characterized by increasing activity during relaxation, and decreasing activity during stress [16]. However, alpha is not the only band that can indicate mental stress. The beta band has also been found to convey signs of mental stress; an increase of power in the beta band is associated with increased alertness when performing cognitive tasks. A relationship between stress and beta band activity at the anterior temporal lobe has been demonstrated when stress-inducing pictures are shown [8, 12, 17]. Meanwhile, theta band activity has been used to assess stress during mental arithmetic tasks [18]. Moreover, gamma band activity related to slow bands has also been proposed as a biomarker for the identification of stress [19].

Previous studies have demonstrated the feasibility of using EEG for chronic stress assessment. Chronic stress, unlike acute stress, can be measured without stress-inducing tasks. Since chronic stress is a more related to depressive symptoms than acute stress [5], and since EEG may be useful as a stress indicator in everyday life [7], we propose the use of EEG signals to identify chronic stress without inducing stress experimentally.

3 Methodology

3.1 Participants

A total of 55 healthy participants (30 male, 25 female) with ages ranging from 21 to 45 years (Mean $= 26, SD = 4.84$) participated in the study. The participants were informed to avoid food and drink with caffeine as well as conditioners, hair creams, sprays, or styling gels on the day of the experiment. Prior to the experiment, all participants gave consent in writing before completing the questionnaire and having their EEG recorded.

3.2 Data Acquisition

The EEG acquisition phase of the experiment was conducted in a room with a controlled environment. An EEG electrode cap kit was used to record EEG signals of the participants at 125 Hz at 16 active points, namely FP1, FP2, F3, F4, F7, F8, C3, C4, T3, T4, T5, T6, P3, P4, O1, and O2, with two reference electrodes according to the electrode locations of the international 10 - 20 system for EEG (Figure 4). The experimental procedure is shown in Figure 3. All participants were initially instructed regarding the experimental procedure, signed the consent form, then took the PSS questionnaire. Each participant was placed comfortably in a chair and asked to close their eyes for 10 minutes while keeping their head motionless to eliminate movement artifacts. The closed-eyes condition was utilized to simplify data processing (obviating the need to remove blink artifact). This design is consistently with previous research that has found that chronic stress can be predicted from EEG without stress induction [1, 7, 20].

In the study, the PSS-10 questionnaire was used to assess and classify participants' stress levels. The questionnaire has 10 questions, each of which asks about the frequency of stress the subject has experienced in the last month. Each question is answered on a scale of 0 (the incident never happened), to 4 (it occurs frequently). The group of participants was partitioned into three groups based on their PSS scores, as either stressed, non-stressed, or neutral [TODO]. PSS thresholds were chosen as

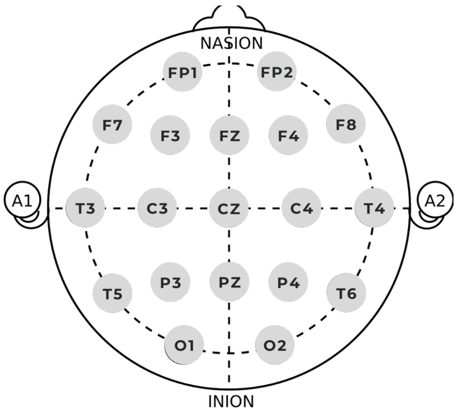
$$T_u = \mu + \frac{\sigma}{2} \tag{1}$$

$$T_l = \mu - \frac{\sigma}{2}, \tag{2}$$

where μ is the mean and σ is the standard deviation of the full group's PSS scores over all 55 participants, T_u is the upper threshold, and T_l is the lower threshold. Any participants with PSS score lower than T_l were labeled as non-stressed, and those with PSS scores higher than T_u were labeled as stressed. Participants in the intermediary range were labeled as neutral and not used in the feature selection or classification experiment.

Fig. 3: Experimental procedure and data acquisition process

Fig. 4: Electrode locations of International 10-20 system for EEG recording [21].



3.3 Feature Extraction

The first five minutes of the participants' rest-state EEG signals were segmented into 20 smaller records (15 seconds each). For each record, the five EEG frequency bands were obtained using the `psd_welch` function from in the `mne` library. The function calculates power spectral density (PSD) of multiple smaller windows and average them to get a smoother result. The frequency bands, namely, delta (1-3 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz), gamma (25-43 Hz), slow (4-13 Hz), and beta$_{\text{low}}$ (13-17 Hz) were computed from each electrode. We did not perform any other preprocessing. The ratio of gamma to slow bands was used to calculate the gamma$_{\text{relative}}$ feature. Moreover, there were five alpha and beta asymmetries. The following formulae were used to compute the alpha asymmetries:

$$\alpha_f = \frac{\mathrm{F4}_\alpha - \mathrm{F3}_\alpha}{\mathrm{F4}_\alpha + \mathrm{F3}_\alpha} \tag{3}$$

$$\alpha_t = \frac{\mathrm{T4}_\alpha - \mathrm{T3}_\alpha}{\mathrm{T4}_\alpha + \mathrm{T3}_\alpha} \tag{4}$$

$$\alpha_a = \alpha_f + \alpha_t \tag{5}$$

α_f, α_t and α_a indicate frontal, temporal, and alpha asymmetries, respectively, and channel$_\alpha$ denotes the PSD of alpha at each electrode. The beta asymmetry was computed over the frontal and temporal region using the same procedure:

$$\beta_f = \frac{\mathrm{F4}_\beta - \mathrm{F3}_\beta}{\mathrm{F4}_\beta + \mathrm{F3}_\beta} \tag{6}$$

$$\beta_t = \frac{\mathrm{T4}_\beta - \mathrm{T3}_\beta}{\mathrm{T4}_\beta + \mathrm{T3}_\beta} \tag{7}$$

β_f and β_t indicate frontal and temporal asymmetries of the beta band, and channel$_\beta$ denotes the PSD of beta at each electrode.

In total, we extracted $(16 \times 8) + 5 = 133$ features.

3.4 Feature Selection

We normalized each of the 133 features across the entire dataset using z-scaling:

$$\mathbf{X}'_i = \frac{\mathbf{X}_i - \mu_i}{\sigma_i}, \tag{8}$$

where μ_i is the mean and σ_i is the standard deviation of the data for feature i over all samples across the entire dataset.

Next, we eliminated features unlikely to be useful for classification by comparing the conditional means of each feature over each class (more stressed and less stressed) separately using t-tests for the null hypothesis of equal means. From the original 133 features, we found that 25 of t-tests gave $p < .001$, so we retained these 25 features for further consideration.

We then ranked the 25 features using seven methods:

1. Rank$_{\text{Baseline}}$: ¡Will investigate t-value¿.
2. Rank$_{\text{LR}}$: ranked according to the absolute value of the logistic regression coefficient assigned to the feature.
3. Rank$_{\text{LDA}}$: ranked according to the absolute value of the linear discriminant analysis coefficient assigned to the feature.

4. Rank_{AB}: ranked according to the feature importance score given by AdaBoost. The importance score is the sum of the weight of each weak classifier utilizing the feature in question. [TODO: Recheck]
5. Rank_{GB}: ranked according to the feature importance score given by gradient boosting. The importance score is the sum of the weight of each weak classifier utilizing the feature in question. [TODO: Recheck]
6. Rank_{RF}: ranked according to the feature importance score given by random forest. The importance score is the sum of the weight of each weak classifier utilizing the feature in question. [TODO: Recheck]
7. $\text{Rank}_{\text{Ensemble}}$: ranked according to a score based on the previous five rankings. The score for feature i is

$$\text{score}_i = \sum_{m \in M} \text{Rank}_m[i], \tag{9}$$

where $M = \{\text{LR}, \text{LDA}, \text{AB}, \text{GB}, \text{RF}\}$, and i is the index of the feature of interest. $\text{Rank}_{\text{Ensemble}}$ is obtained by sorting the scores in ascending order. Thus, the feature with the lowest score (summed rank) is the most important one.

3.5 Classification

We utilize two classifiers commonly used in previous studies [7, 14, 22, 23]: logistic regression (LR) and the support vector machine (SVM).

3.5.1 Logistic Regression (LR)

In its simplest form, logistic regression is a generalized linear model for the Bernoulli (binary class) distribution that employs a logistic sigmoid in a linear combination of the features to represent a binary dependent variable i.e., p(y|x).

3.5.2 Support Vector Machine (SVM)

A support vector machine performs linear binary maximum margin classification in a feature space. SVMs have been shown to be very effective in EEG-based stress categorization studies [14, 22]. A linear SVM would give a similar result to LR, but with a nonlinear transformation into feature space, SVMs can give higher accuracy.

[TODO: Add LDA, Ada, RF, Boost]

[Start from here]

3.6 Performance Metrics

A 10-CV score is used to measure the classification performance. t-SNE is used to visualize the similarity between samples.

4 Results

4.1 Groups Labeling

The total number of 55 participants are divided into three groups: Stressed, Non-Stressed, and Neutral groups based on the PSS questionnaire score as describe in the section [TODO]. From the Equation 1 and 2, we obtained statistics μ, $\sigma = (20.75 \pm 6.13)$. Participants scoring below 17.68 are considered Non-Stressed, whereas participants scoring higher than 23.81 are considered Stressed group. Participants scoring with 0.5 standard deviation [TODO] are considered to be in Neutral group and are discarded in the classification. As a result, the Stress group comprises 20 participants, while Non-Stress group comprises 16 participants. In total, the number of subjects in classification is $(20 + 16) = 36$ and $(36 \times 20) = 720$ samples after segmentation.

4.2 t-test result

As described in the section [TODO], Independent sample two-tailed t-tests with $p < .001$ were used to select any feature set study. For the t-test, the degree of freedom was 1 and the null hypothesis was tested for EEG feature of Stress and Non-Stress groups. The result using the p-values for different features are shown in Table 1 and Table 2.

Table 1: Results for t-tests on various frequency bands.

	Frequency bands							
Channel	**Delta (δ)**	**Theta (θ)**	**Alpha (α)**	**Beta (β)**	**Gamma (γ)**	**Slow**	**Low Beta**	**RG**
FP1	**<.001**	0.744	**0.002**	0.899	**0.024**	0.203	0.629	0.221
FP2	**0.016**	**0.010**	**0.041**	**0.008**	0.956	0.682	0.071	0.168
F3	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	**<.001**	0.864
F4	**<.001**	**0.001**	**<.001**	0.488	0.276	**0.020**	0.479	**0.011**
F7	**0.006**	0.550	**<.001**	**0.015**	0.616	**0.026**	0.474	**0.011**
F8	0.115	0.211	0.088	**0.045**	0.251	0.789	0.117	0.677
C3	**<.001**	**<.001**	0.297	0.069	**0.007**	**0.026**	**0.003**	**<.001**
C4	0.551	0.329	0.316	0.895	**0.016**	0.297	0.186	0.146
T3	0.090	0.719	**0.001**	0.650	**<.001**	0.401	0.608	0.078
T4	0.101	**<.001**	0.855	**0.029**	**0.003**	**0.003**	**<.001**	**0.001**
T5	0.095	0.126	0.213	0.217	0.305	0.482	0.687	0.199
T6	0.919	0.840	**<.001**	0.306	**0.003**	**0.010**	**0.014**	0.105
P3	0.639	0.507	0.405	0.114	0.068	0.424	0.077	0.358
P4	**<.001**	**<.001**	**<.001**	0.573	**0.012**	0.630	0.379	0.165
O1	0.057	0.169	0.080	0.271	0.128	0.163	0.778	0.469
O2	**0.001**	0.384	0.388	**0.009**	0.544	0.729	0.252	**0.042**

Table 2: Results for the t-test on asymmetries

Alpha asymmetry (α_a)	**Alpha frontal (α_f)**	**Alpha temporal (α_t)**	**Beta frontal (β_f)**	**Beta temporal (β_f)**
<.001	**<.001**	**<.001**	**<.001**	**0.002**

A total of 25 features had $p < .001$, namely FP1$_\delta$, F3$_\delta$, F4$_\delta$, C3$_\delta$, P4$_\delta$, F3$_\theta$, C3$_\theta$, T4$_\theta$, P4$_\theta$, F3$_\alpha$, F4$_\alpha$, F7$_\alpha$, T6$_\alpha$, P4$_\alpha$, F3$_\beta$, F3$_\gamma$, T3$_\gamma$, F3$_{\text{slow}}$, F3$_{\text{Low}\beta}$, T4$_{\text{Low}\beta}$, C3$_{\text{RG}}$, α_f, α_t, α_a,β_f. We use this list as the baseline ranking (Rank$_{\text{Baseline}}$).

4.3 Ranking with coefficient and feature importance score

We next ranked the 25 features selected by the t-test result using feature importance scores for the classifiers mentioned in the Section 3.4. To verify any Rank_m where $m \in \{\text{LR}, \text{LDA}, \text{ADA}, \text{GB}, \text{RF}\}$, we (1) iterate over the index from Rank_m; (2) select features from Rank_m^1 to Rank_m^i, where i is the index of the current iteration; (3) calculate 10-CV scores for RBF-SVM and LR; and (4) plot the t-SNE space to visualize the similarity of sample embeddings given the features from the iteration in which the SVM achieves a 0.9 10-CV score.

The 10-CV score thresholds of 0.9 for the SVM models and 0.8 for the LR models were selected based on the 10-CV score of each model when trained using 25 features. In this preliminary experiment, the SVM exceeded 0.9 10-CV score, while LR could only reach 0.85 at best. Table [TODO] that reports every ranks and 10-CV score of all classifiers can be found in Appendix A.

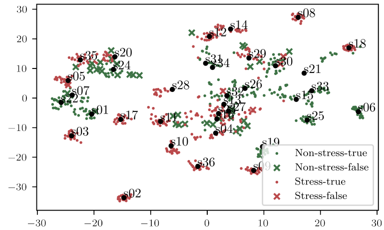
4.3.1 Baseline

When using $\text{Rank}_{\text{Baseline}}$, the RBF-SVM could achieve a 0.9 10-CV score with the top eight features, FP1_δ, F3_δ, F4_δ, C3_δ, P4_δ, F3_θ, C3_θ, and T4_θ, as shown in Table 3. Using the same rank with LR, however, the model required the top 16 features to reach a 0.8 10-CV score.

Table 3: The 10-CV score of each classifier when using $\text{Rank}_{\text{Baseline}}$ as a rank. The model is trained on a list of features from Rank^1 to Rank^i. [TODO]

i	$\text{Rank}_{\text{Baseline}}$	SVM	LR
1	FP1_δ	0.621±0.046	0.578±0.054
2	F3_δ	0.740±0.061	0.678±0.055
3	F4_δ	0.769±0.043	0.667±0.062
4	C3_δ	0.829±0.044	0.678±0.077
5	P4_δ	0.868±0.051	0.728±0.064
6	F3_θ	0.875±0.041	0.722±0.049
7	C3_θ	0.890±0.020	0.724±0.043
8	T4_θ	**0.915±0.031**	0.764±0.033
9	P4_θ	0.919±0.012	0.753±0.032
10	F3_α	0.931±0.020	0.774±0.041
11	F4_α	0.928±0.024	0.796±0.027
12	F7_α	0.933±0.028	0.781±0.048
13	T6_α	0.946±0.031	0.790±0.036
14	P4_α	0.956±0.016	0.783±0.045
15	F3_β	0.961±0.023	0.788±0.041
16	F3_γ	0.978±0.015	**0.815±0.037**
17	T3_γ	0.976±0.023	0.811±0.044
18	F3_{slow}	0.974±0.015	0.808±0.040
19	$\text{F3}_{\text{Low}\beta}$	0.976±0.011	0.811±0.040
20	$\text{T4}_{\text{Low}\beta}$	0.982±0.014	0.825±0.058
21	C3_{RG}	0.981±0.013	0.838±0.022
22	α_f	0.979±0.007	0.824±0.041
23	α_t	0.981±0.009	0.833±0.037
24	α_a	0.978±0.013	0.838±0.031
25	β_f	0.979±0.014	0.844±0.040

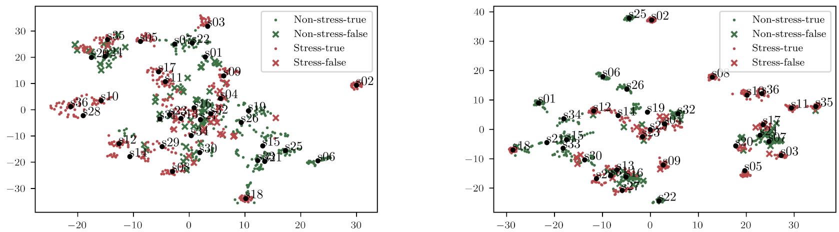
Fig. 5: The data plot in t-SNE space using top eight features from $\text{Rank}_{\text{Baseline}}$. Although the rbf-SVM achieves 0.915 10-CV score, the data are not separated. This affect the LR performace as shown in Table 3



4.3.2 Logistic Regression Coefficient Ranking

Table 4 shows the results we obtain using the ranking of features by the logistic regression coefficient. With this ranking, the SVM was able to achieve 0.9 10-CV score with only six features. The LR classifier also reached a 0.8 10-CV score using the top nine features, seven features fewer than with $\text{Rank}_{\text{Baseline}}$. The top six features according to Rank_{LR} are $F3_\beta$, $P4_\delta$, β_f, $C3_{\text{RG}}$, $F3_\delta$, $F4_\delta$, and $T4_\theta$.

Fig. 6: The top six features from $\text{Rank}_{\text{Baseline}}$ and Rank_{LR} plot in t-SNE space. The two groups are better separated in the case of Rank_{LR}.



(a) Baseline (b) LR

4.3.3 Ensemble

Scores for the $\text{Rank}_{\text{Ensemble}}$ ranking were calculated following Equation 9. Table 5 shows the calculated scores and ranks them accordingly. In this configuration, the SVM with the top six features [TODO] achieves 0.899 ± 0.040 10-CV score and, later, achieves over 0.9 10-CV score at iteration eight. The top eight features are β_f, $F3_\delta$, $F4_\delta$, $F3_\beta$, $P4_\delta$, $F3_\gamma$, $P4_\theta$, and $C3_\theta$.

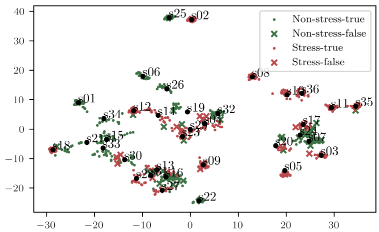
Table 4: The 10-CV score of each classifier when using Rank_{LR} as a rank. The model is trained on a list of features from Rank^1 to Rank^i where i is the row number.

No.	Rank_{LR}	coeff	SVM	LR
1	$F3_\beta$	1.894	0.575±0.051	0.558±0.040
2	$P4_\delta$	1.651	0.635±0.050	0.571±0.048
3	β_f	-1.435	0.749±0.058	0.624±0.051
4	$C3_{\text{RG}}$	-1.346	0.858±0.034	0.646±0.032
5	$F3_\delta$	-1.273	0.886±0.030	0.718±0.047
6	$F4_\delta$	-1.258	**0.900±0.042**	0.735±0.061
7	$T4_\theta$	0.952	0.910±0.029	0.735±0.053
8	$F3_{\text{Low}\beta}$	-0.841	0.921±0.037	0.765±0.054
9	$P4_\alpha$	-0.833	0.961±0.014	**0.836±0.040**
10	$F7_\alpha$	0.767	0.961±0.022	0.832±0.040
11	$F4_\alpha$	-0.609	0.960±0.018	0.846±0.048
12	$F3_\alpha$	-0.594	0.961±0.016	0.858±0.045
13	$FP1_\delta$	-0.503	0.964±0.015	0.849±0.052
14	$T6_\alpha$	-0.465	0.957±0.015	0.854±0.019
15	$F3_\gamma$	0.422	0.957±0.031	0.856±0.032
16	$P4_\theta$	0.405	0.971±0.018	0.851±0.049
17	$T4_{\text{Low}\beta}$	0.396	0.968±0.019	0.850±0.041
18	$F3_\theta$	-0.384	0.969±0.016	0.854±0.037
19	$C3_\delta$	0.350	0.982±0.013	0.846±0.036
20	$C3_\theta$	-0.348	0.979±0.016	0.847±0.020
21	$T3_\gamma$	-0.323	0.979±0.011	0.850±0.034
22	α_t	-0.201	0.975±0.019	0.853±0.034
23	α_a	-0.182	0.981±0.023	0.853±0.035
24	α_f	-0.067	0.979±0.017	0.847±0.052
25	$F3_{\text{slow}}$	0.036	0.975±0.015	0.840±0.042

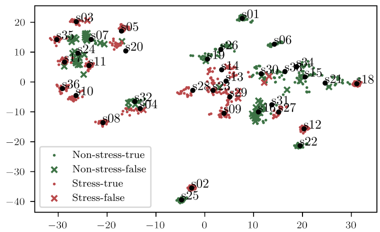
Table 5: The 10-CV score of each classifier when using $\mathrm{Rank}_{\mathrm{ensemble}}$ as a rank. The model is trained on a list of features from Rank^1 to Rank^i where i is the row number.

No.	$\mathrm{Rank}_{\mathrm{ensemble}}$	score	SVM	LR
1	β_f	15	0.693±0.057	0.669±0.046
2	$\mathrm{F3}_\delta$	18	0.765±0.029	0.731±0.048
3	$\mathrm{F4}_\delta$	34	0.775±0.057	0.725±0.035
4	$\mathrm{F3}_\beta$	34	0.849±0.040	0.743±0.047
5	$\mathrm{P4}_\delta$	45	0.867±0.044	0.728±0.070
6	$\mathrm{F3}_\gamma$	47	0.899±0.040	0.735±0.033
7	$\mathrm{P4}_\theta$	48	0.890±0.040	0.754±0.041
8	$\mathrm{C3}_\theta$	49	**0.925±0.023**	0.782±0.058
9	$\mathrm{C3}_{\mathrm{RG}}$	52	0.944±0.030	0.775±0.030
10	$\mathrm{T4}_\theta$	54	0.947±0.017	0.794±0.050
11	$\mathrm{T4}_{\mathrm{Low}\beta}$	54	0.958±0.023	0.797±0.058
12	$\mathrm{P4}_\alpha$	57	0.971±0.020	**0.811±0.060**
13	$\mathrm{F7}_\alpha$	57	0.975±0.025	0.815±0.050
14	$\mathrm{F3}_\alpha$	59	0.972±0.025	0.838±0.040
15	$\mathrm{F3}_\theta$	61	0.976±0.021	0.849±0.034
16	$\mathrm{C3}_\delta$	61	0.978±0.023	0.849±0.058
17	$\mathrm{F4}_\alpha$	67	0.978±0.015	0.844±0.056
18	$\mathrm{F3}_{\mathrm{Low}\beta}$	69	0.979±0.018	0.849±0.036
19	$\mathrm{T3}_\gamma$	71	0.981±0.013	0.840±0.035
20	$\mathrm{T6}_\alpha$	73	0.981±0.015	0.850±0.053
21	$\mathrm{FP1}_\delta$	79	0.979±0.009	0.844±0.037
22	$\mathrm{F3}_{\mathrm{slow}}$	88	0.981±0.013	0.844±0.040
23	α_f	94	0.981±0.011	0.854±0.036
24	α_a	103	0.979±0.013	0.850±0.038
25	α_t	111	0.978±0.015	0.844±0.020

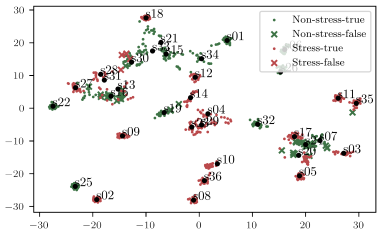
Fig. 7: The top six and top eight features from Rank_{LR} and $\text{Rank}_{\text{Ensemble}}$ plot in t-SNE space.



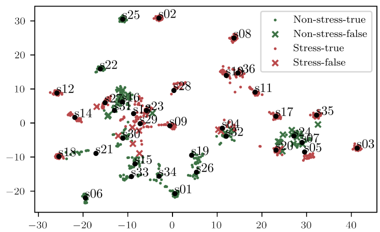
(a) Top six features according to LR.



(b) top six Ensemble



(c) top eight LR



(d) top eight Ensemble

5 Discussion

At the recording state, we chose to do eye-closed conditions because we want to avoid external factors such as lighting conditions and visual distraction, as well as eye artifacts. However, there are challenges to this approach. First, during closing the eye, the power of the Alpha band in the occipital area is greatly increased. We could argue that this does not affect our result but due to the nature of EEG, the Alpha information in the occipital area could contaminate their neighbor. Maybe this is the reason why any of the Alpha asymmetry features are staying at the bottom of the rank. Second, the participant might fall asleep during the record. Because the record session is five minutes long and the participant is asked to avoid any form of caffeine which many of them have on a daily basis, closing the eyes for five minutes is enough to turn some participants into a relaxing or sleeping state.

All 55 participants can be considered well educated since all of them are, at least, pursuing a degree of bachelor. The nationality range is limited to Asian and the age is between 20 and 40 years old. Our data is somewhat biased by this fact.

The label of the data is based on the questionnaire PSS-10 score, a method subject to error and manipulation. The analysis could be improved if a psychologist expert is involved in the labeling process. Because of our labeling method, our data has a minor imbalance issue which we chose to ignore (16 Non-stress and 20 Stress participants). Our suggestion would be to increase the lower threshold to accommodate more Non-stress samples or we could segment the two groups differently.

In our experiment, RBF-SVM shows to be the best classifier for chronic stress. However, because of the nature of the RBF kernel, we can not rank the features by importance. To be specific, given enough data dimension, RBF-SVM always achieves a 0.9 10-CV score. While we could brute force through every combination of features given enough time, we can not be sure that the model learns chronic stress patterns or participant-specific patterns. Because of this reason, t-SNE is utilized.

We, first, investigated the Logistic Regression Coefficient and found that, in t-SNE space, the two groups are well separated as shown in Figure 6. In addition, the performance of other models is also improved given a smaller set of features (Table A2). Therefore, we extend our idea to other models and, finally, convolute all ranks into the $\text{Rank}_{\text{Ensemble}}$. Every classifier seems to agree that the Beta and Delta band are the most important frequency. The electrode F3 is the most important followed by F4 and P4. Our result agrees with the previous studies [7]

Furthermore, t-SNE plots seem to suggest that our data has an outlier, for instance, s07 and s24 consistently appear in the middle of the stress group. To confirm this assumption, a larger and broader group of participants is needed.

6 Conclusion

In conclusion, the rest-state EEG can be used to classify chronic stress. The classification result shows that SVM with rbf kernel achieves over 0.98 10-CV scores and LR achieves 0.85 using all features with $p < .001$ from the reported t-test result. Extended ranking with various classifiers improve the feature selection and help to narrow down the feature list. Finally, convoluted $\text{Rank}_{\text{Ensemble}}$ shows the top eight Chronic Stress features which are β_f, F3_δ, F4_δ, F3_β, P4_δ, F3_γ, P4_θ, and C3_θ. With these eight features, rbf-SVM, ADA, GB, and RF achieve over 0.9 10-CV score while adding the next four features (C3_{RG}, T4_θ, $\text{T4}_{\text{Low}\beta}$, and P4_α), helps LR and LDA to achieve over 0.8 10-CV score (Table A7).

Appendix A 10-CV result of each Ranks

Fig. A1: A bump chart of features in each ranking.

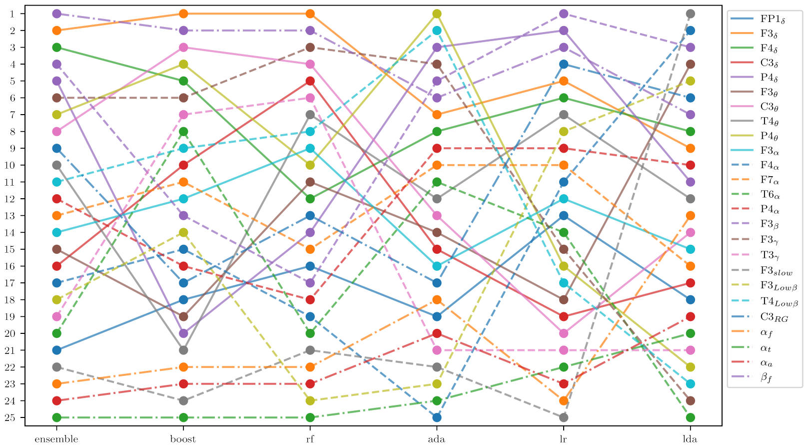


Table A1: The 10-CV score of each classifier when using $\text{Rank}_{\text{baseline}}$ as a rank.

No.	$\text{Rank}_{\text{baseline}}$	SVM	LR	GB	ADA	RF	LDA
1	$FP1_\delta$	0.621±0.046	0.578±0.054	0.606±0.030	0.604±0.036	0.525±0.045	0.585±0.044
2	$F3_\delta$	0.740±0.061	0.678±0.055	0.733±0.047	0.710±0.049	0.724±0.061	0.676±0.045
3	$F4_\delta$	0.769±0.043	0.667±0.062	0.765±0.047	0.714±0.037	0.761±0.028	0.664±0.039
4	$C3_\delta$	0.829±0.044	0.678±0.077	0.832±0.038	0.761±0.036	0.843±0.028	0.675±0.043
5	$P4_\delta$	0.868±0.051	0.728±0.064	0.868±0.030	0.807±0.043	0.885±0.036	0.733±0.036
6	$F3_\theta$	0.875±0.041	0.722±0.049	0.853±0.050	0.821±0.074	0.878±0.058	0.724±0.055
7	$C3_\theta$	0.890±0.020	0.724±0.043	0.875±0.032	0.833±0.046	0.897±0.040	0.722±0.046
8	$T4_\theta$	**0.915±0.031**	0.764±0.033	0.883±0.052	0.843±0.030	**0.907±0.030**	0.751±0.054
9	$P4_\theta$	0.919±0.012	0.753±0.032	**0.901±0.021**	0.840±0.027	0.911±0.045	0.765±0.052
10	$F3_\alpha$	0.931±0.020	0.774±0.041	0.918±0.027	0.878±0.039	0.926±0.021	0.778±0.050
11	$F4_\alpha$	0.928±0.024	0.796±0.027	0.931±0.026	0.876±0.030	0.936±0.026	**0.800±0.035**
12	$F7_\alpha$	0.933±0.028	0.781±0.048	0.928±0.028	0.867±0.034	0.939±0.028	0.793±0.032
13	$T6_\alpha$	0.946±0.031	0.790±0.036	0.940±0.019	0.869±0.038	0.936±0.036	0.789±0.042
14	$P4_\alpha$	0.956±0.016	0.783±0.045	0.933±0.027	0.899±0.037	0.947±0.024	0.788±0.030
15	$F3_\beta$	0.961±0.023	0.788±0.041	0.940±0.028	0.882±0.041	0.957±0.020	0.769±0.033
16	$F3_\gamma$	0.978±0.015	**0.815±0.037**	0.951±0.022	**0.924±0.029**	0.969±0.022	0.814±0.032
17	$T3_\gamma$	0.976±0.023	0.811±0.044	0.956±0.030	0.912±0.027	0.975±0.015	0.814±0.044
18	$F3_{\text{slow}}$	0.974±0.015	0.808±0.040	0.961±0.025	0.914±0.031	0.968±0.024	0.817±0.047
19	$F3_{\text{Low}\beta}$	0.976±0.011	0.811±0.040	0.960±0.020	0.911±0.024	0.971±0.025	0.808±0.042
20	$T4_{\text{Low}\beta}$	0.982±0.014	0.825±0.058	0.958±0.012	0.918±0.027	0.974±0.013	0.812±0.051
21	$C3_{\text{RG}}$	0.981±0.013	0.838±0.022	0.958±0.020	0.904±0.021	0.971±0.018	0.814±0.043
22	α_f	0.979±0.007	0.824±0.041	0.962±0.015	0.912±0.036	0.975±0.020	0.819±0.041
23	α_t	0.981±0.009	0.833±0.037	0.964±0.015	0.924±0.032	0.969±0.021	0.821±0.042
24	α_a	0.978±0.013	0.838±0.031	0.968±0.022	0.914±0.037	0.979±0.016	0.826±0.031
25	β_f	0.979±0.014	0.844±0.040	0.961±0.022	0.917±0.037	0.972±0.014	0.831±0.033

Table A2: The 10-CV score of each classifier when using $\mathrm{Rank}_{\mathrm{LR}}$ as a rank.

No.	$\mathrm{Rank}_{\mathrm{LR}}$	coeff	SVM	LR	GB	ADA	RF	LDA
1	$\mathrm{F3}_{\beta}$	1.894	0.575±0.051	0.558±0.040	0.561±0.072	0.607±0.075	0.564±0.057	0.565±0.046
2	$\mathrm{P4}_{\delta}$	1.651	0.635±0.050	0.571±0.048	0.656±0.033	0.610±0.054	0.693±0.036	0.571±0.047
3	β_f	-1.435	0.749±0.058	0.624±0.051	0.753±0.047	0.742±0.039	0.814±0.055	0.624±0.054
4	$\mathrm{C3}_{\mathrm{RG}}$	-1.346	0.858±0.034	0.646±0.032	0.856±0.032	0.781±0.034	0.885±0.035	0.647±0.044
5	$\mathrm{F3}_{\delta}$	-1.273	0.886±0.030	0.718±0.047	0.875±0.052	0.826±0.044	0.897±0.019	0.715±0.024
6	$\mathrm{F4}_{\delta}$	-1.258	**0.900±0.042**	0.735±0.061	0.899±0.028	0.850±0.035	**0.912±0.028**	0.749±0.015
7	$\mathrm{T4}_{\theta}$	0.952	0.910±0.029	0.735±0.053	**0.900±0.038**	0.865±0.036	0.922±0.044	0.754±0.041
8	$\mathrm{F3}_{\mathrm{Low}\beta}$	-0.841	0.921±0.037	0.765±0.054	0.896±0.052	0.868±0.037	0.931±0.039	0.761±0.044
9	$\mathrm{P4}_{\alpha}$	-0.833	0.961±0.014	**0.836±0.040**	0.931±0.026	0.888±0.033	0.940±0.018	**0.836±0.046**
10	$\mathrm{F7}_{\alpha}$	0.767	0.961±0.022	0.832±0.040	0.932±0.035	0.893±0.036	0.960±0.028	0.835±0.067
11	$\mathrm{F4}_{\alpha}$	-0.609	0.960±0.018	0.846±0.048	0.947±0.024	0.893±0.031	0.946±0.021	0.840±0.049
12	$\mathrm{F3}_{\alpha}$	-0.594	0.961±0.016	0.858±0.045	0.942±0.024	**0.900±0.025**	0.949±0.027	0.846±0.040
13	$\mathrm{FP1}_{\delta}$	-0.503	0.964±0.015	0.849±0.052	0.938±0.021	0.908±0.031	0.953±0.021	0.839±0.037
14	$\mathrm{T6}_{\alpha}$	-0.465	0.957±0.015	0.854±0.019	0.939±0.031	0.917±0.032	0.951±0.024	0.836±0.043
15	$\mathrm{F3}_{\gamma}$	0.422	0.957±0.031	0.856±0.032	0.956±0.024	0.912±0.035	0.964±0.020	0.842±0.045
16	$\mathrm{P4}_{\theta}$	0.405	0.971±0.018	0.851±0.049	0.951±0.027	0.935±0.026	0.967±0.017	0.846±0.024
17	$\mathrm{T4}_{\mathrm{Low}\beta}$	0.396	0.968±0.019	0.850±0.041	0.961±0.010	0.922±0.036	0.968±0.028	0.839±0.048
18	$\mathrm{F3}_{\theta}$	-0.384	0.969±0.016	0.854±0.037	0.962±0.018	0.935±0.021	0.968±0.014	0.838±0.064
19	$\mathrm{C3}_{\delta}$	0.350	0.982±0.013	0.846±0.036	0.962±0.021	0.938±0.027	0.972±0.021	0.843±0.033
20	$\mathrm{C3}_{\theta}$	-0.348	0.979±0.016	0.847±0.020	0.951±0.029	0.936±0.017	0.967±0.021	0.831±0.034
21	$\mathrm{T3}_{\gamma}$	-0.323	0.979±0.011	0.850±0.034	0.957±0.025	0.939±0.029	0.974±0.020	0.835±0.023
22	α_t	-0.201	0.975±0.019	0.853±0.034	0.962±0.033	0.925±0.033	0.969±0.018	0.829±0.038
23	α_a	-0.182	0.981±0.023	0.853±0.035	0.954±0.014	0.917±0.039	0.976±0.025	0.829±0.036
24	α_f	-0.067	0.979±0.017	0.847±0.052	0.964±0.029	0.919±0.031	0.976±0.012	0.826±0.040
25	$\mathrm{F3}_{\mathrm{slow}}$	0.036	0.975±0.015	0.840±0.042	0.956±0.018	0.925±0.021	0.974±0.016	0.833±0.041

Table A3: The 10-CV score of each classifier when using $\mathrm{Rank}_{\mathrm{LDA}}$ as a rank.

No.	$\mathrm{Rank}_{\mathrm{LDA}}$	score	SVM	LR	GB	ADA	RF	LDA
1	$\mathrm{F3}_{\mathrm{slow}}$	4.658	0.603±0.044	0.589±0.046	0.593±0.052	0.592±0.059	0.610±0.055	0.583±0.043
2	$\mathrm{F4}_{\alpha}$	-3.383	0.707±0.040	0.640±0.055	0.703±0.063	0.682±0.050	0.706±0.053	0.643±0.058
3	$\mathrm{F3}_{\beta}$	3.258	0.726±0.038	0.658±0.049	0.758±0.051	0.718±0.046	0.783±0.038	0.650±0.064
4	$\mathrm{F3}_{\theta}$	-2.143	0.749±0.049	0.633±0.039	0.800±0.024	0.729±0.053	0.818±0.043	0.629±0.041
5	$\mathrm{F3}_{\mathrm{Low}\beta}$	-1.710	0.753±0.046	0.651±0.044	0.788±0.032	0.775±0.041	0.804±0.049	0.649±0.066
6	$\mathrm{C3}_{\mathrm{RG}}$	-1.595	0.800±0.042	0.679±0.049	0.808±0.044	0.738±0.045	0.847±0.041	0.674±0.044
7	β_f	-1.398	0.854±0.049	0.707±0.041	0.882±0.027	0.824±0.025	0.886±0.038	0.725±0.043
8	$\mathrm{F4}_{\delta}$	-1.289	0.883±0.048	0.714±0.053	0.886±0.044	0.856±0.037	**0.917±0.026**	0.725±0.026
9	$\mathrm{F3}_{\delta}$	-1.227	0.897±0.031	0.767±0.057	0.893±0.030	0.868±0.023	0.912±0.041	0.782±0.026
10	$\mathrm{P4}_{\alpha}$	-1.155	**0.911±0.022**	0.783±0.042	**0.910±0.030**	0.867±0.050	0.918±0.040	0.785±0.058
11	$\mathrm{P4}_{\delta}$	1.143	0.958±0.022	**0.828±0.039**	0.925±0.030	0.892±0.036	0.944±0.022	**0.832±0.034**
12	$\mathrm{T4}_{\theta}$	1.069	0.960±0.027	0.849±0.037	0.947±0.022	0.899±0.035	0.954±0.022	0.844±0.044
13	α_f	-1.042	0.957±0.027	0.850±0.029	0.942±0.019	**0.906±0.037**	0.953±0.026	0.844±0.046
14	$\mathrm{C3}_{\theta}$	-0.639	0.972±0.020	0.850±0.048	0.943±0.027	0.915±0.024	0.967±0.021	0.838±0.044
15	$\mathrm{F3}_{\alpha}$	-0.458	0.975±0.021	0.847±0.033	0.944±0.029	0.914±0.044	0.960±0.018	0.839±0.034
16	$\mathrm{F7}_{\alpha}$	0.395	0.976±0.014	0.851±0.042	0.946±0.031	0.914±0.030	0.961±0.023	0.835±0.032
17	$\mathrm{C3}_{\delta}$	0.364	0.972±0.022	0.851±0.045	0.946±0.025	0.919±0.028	0.968±0.020	0.833±0.024
18	$\mathrm{FP1}_{\delta}$	-0.339	0.975±0.016	0.850±0.038	0.950±0.039	0.890±0.031	0.960±0.023	0.832±0.038
19	α_a	-0.279	0.979±0.019	0.839±0.044	0.946±0.023	0.915±0.031	0.961±0.025	0.835±0.036
20	α_t	0.271	0.974±0.025	0.847±0.025	0.953±0.029	0.912±0.028	0.972±0.015	0.836±0.043
21	$\mathrm{T3}_{\gamma}$	0.180	0.978±0.019	0.849±0.034	0.953±0.020	0.904±0.029	0.974±0.021	0.835±0.040
22	$\mathrm{P4}_{\theta}$	0.077	0.974±0.015	0.849±0.034	0.947±0.039	0.910±0.044	0.968±0.018	0.838±0.044
23	$\mathrm{T4}_{\mathrm{Low}\beta}$	0.066	0.979±0.017	0.849±0.024	0.953±0.026	0.911±0.032	0.978±0.015	0.825±0.053
24	$\mathrm{F3}_{\gamma}$	-0.042	0.978±0.015	0.842±0.042	0.964±0.029	0.925±0.038	0.971±0.034	0.832±0.033
25	$\mathrm{T6}_{\alpha}$	0.022	0.976±0.013	0.847±0.037	0.962±0.019	0.932±0.027	0.975±0.023	0.835±0.051

Table A4: The 10-CV score of each classifier when using Rank_{ADA} as a rank.

No.	Rank_{ADA}	score	SVM	LR	GB	ADA	RF	LDA
1	P4_θ	0.10	0.594±0.070	0.538±0.026	0.571±0.040	0.604±0.044	0.517±0.071	0.539±0.032
2	$\text{T4}_{\text{Low}\beta}$	0.08	0.703±0.041	0.572±0.045	0.656±0.065	0.633±0.029	0.636±0.054	0.569±0.031
3	P4_δ	0.08	0.742±0.042	0.604±0.035	0.731±0.032	0.682±0.052	0.750±0.046	0.599±0.052
4	F3_γ	0.08	0.835±0.026	0.610±0.051	0.879±0.028	0.774±0.054	0.893±0.027	0.612±0.047
5	F3_β	0.08	0.853±0.026	0.633±0.055	0.899±0.038	0.794±0.037	**0.915±0.038**	0.621±0.041
6	β_f	0.08	0.893±0.030	0.678±0.050	**0.924±0.033**	0.846±0.055	0.940±0.029	0.676±0.048
7	F3_δ	0.06	**0.921±0.033**	0.733±0.044	0.942±0.040	**0.906±0.029**	0.958±0.024	0.739±0.054
8	F4_δ	0.06	0.932±0.037	0.756±0.035	0.947±0.019	0.901±0.027	0.961±0.014	0.769±0.052
9	P4_α	0.06	0.949±0.028	**0.800±0.049**	0.942±0.038	0.917±0.024	0.964±0.021	**0.804±0.054**
10	F7_α	0.06	0.954±0.021	0.807±0.048	0.950±0.025	0.932±0.023	0.964±0.028	0.803±0.054
11	T6_α	0.04	0.958±0.022	0.811±0.038	0.962±0.022	0.921±0.028	0.968±0.016	0.806±0.039
12	T4_θ	0.04	0.964±0.023	0.828±0.049	0.965±0.025	0.928±0.030	0.975±0.017	0.810±0.038
13	C3_θ	0.04	0.976±0.022	0.821±0.031	0.957±0.025	0.926±0.028	0.969±0.014	0.819±0.043
14	F3_θ	0.04	0.979±0.023	0.821±0.058	0.954±0.028	0.933±0.038	0.972±0.026	0.817±0.047
15	C3_δ	0.02	0.981±0.017	0.821±0.048	0.964±0.018	0.944±0.022	0.969±0.016	0.825±0.049
16	F3_α	0.02	0.979±0.025	0.832±0.045	0.956±0.008	0.924±0.035	0.975±0.023	0.833±0.037
17	C3_{RG}	0.02	0.978±0.023	0.846±0.040	0.967±0.019	0.935±0.015	0.975±0.018	0.828±0.030
18	α_f	0.02	0.979±0.014	0.847±0.049	0.957±0.020	0.936±0.021	0.976±0.022	0.825±0.029
19	FP1_δ	0.02	0.979±0.022	0.843±0.044	0.960±0.013	0.929±0.030	0.972±0.023	0.826±0.034
20	α_a	0.00	0.981±0.020	0.846±0.051	0.964±0.021	0.929±0.020	0.975±0.016	0.817±0.043
21	T3_γ	0.00	0.982±0.006	0.843±0.034	0.963±0.022	0.928±0.040	0.978±0.017	0.826±0.046
22	F3_{slow}	0.00	0.981±0.017	0.839±0.057	0.967±0.023	0.924±0.027	0.981±0.021	0.829±0.054
23	$\text{F3}_{\text{Low}\beta}$	0.00	0.982±0.013	0.843±0.036	0.968±0.015	0.914±0.033	0.979±0.014	0.832±0.037
24	α_t	0.00	0.975±0.021	0.847±0.023	0.958±0.032	0.918±0.018	0.983±0.015	0.832±0.015
25	F4_α	0.00	0.975±0.016	0.847±0.022	0.956±0.026	0.906±0.043	0.972±0.020	0.831±0.037

Table A5: The 10-CV score of each classifier when using Rank_{GB} as a rank.

No.	Rank_{GB}	score	SVM	LR	GB	ADA	RF	LDA
1	F3_δ	0.140	0.679±0.049	0.689±0.041	0.668±0.051	0.688±0.047	0.582±0.053	0.688±0.024
2	β_f	0.099	0.767±0.024	0.731±0.050	0.761±0.040	0.749±0.042	0.732±0.049	0.725±0.054
3	C3_θ	0.082	0.810±0.039	0.718±0.031	0.782±0.050	0.806±0.033	0.803±0.032	0.714±0.042
4	P4_θ	0.076	0.836±0.025	0.704±0.040	0.822±0.024	0.831±0.037	0.846±0.036	0.707±0.047
5	F4_δ	0.073	0.858±0.015	0.721±0.054	0.851±0.034	0.836±0.031	0.868±0.025	0.721±0.035
6	F3_γ	0.071	0.894±0.034	0.719±0.049	**0.919±0.037**	0.894±0.029	**0.936±0.021**	0.722±0.046
7	T3_γ	0.069	**0.917±0.030**	0.732±0.049	0.932±0.042	0.892±0.037	0.953±0.022	0.735±0.039
8	T6_α	0.061	0.950±0.026	0.740±0.063	0.933±0.031	**0.910±0.029**	0.956±0.028	0.740±0.072
9	$\text{T4}_{\text{Low}\beta}$	0.050	0.957±0.021	0.778±0.060	0.953±0.027	0.922±0.028	0.956±0.023	0.776±0.035
10	C3_δ	0.040	0.953±0.015	0.776±0.053	0.947±0.036	0.897±0.020	0.954±0.022	0.776±0.040
11	F7_α	0.036	0.960±0.018	0.772±0.059	0.956±0.023	0.919±0.025	0.971±0.020	0.781±0.034
12	F3_α	0.034	0.957±0.024	0.771±0.063	0.947±0.037	0.915±0.029	0.968±0.015	0.788±0.051
13	F3_β	0.026	0.972±0.019	0.779±0.036	0.949±0.029	0.931±0.019	0.976±0.021	**0.801±0.056**
14	$\text{F3}_{\text{Low}\beta}$	0.021	0.974±0.021	0.789±0.043	0.953±0.011	0.921±0.027	0.974±0.015	0.817±0.031
15	F4_α	0.016	0.972±0.024	0.797±0.049	0.956±0.022	0.922±0.032	0.972±0.021	0.822±0.025
16	P4_α	0.015	0.975±0.014	**0.801±0.030**	0.961±0.017	0.938±0.034	0.974±0.024	0.804±0.048
17	C3_{RG}	0.014	0.976±0.016	0.826±0.036	0.957±0.024	0.925±0.029	0.971±0.013	0.817±0.028
18	FP1_δ	0.014	0.972±0.014	0.822±0.051	0.957±0.030	0.929±0.031	0.967±0.014	0.808±0.043
19	F3_θ	0.013	0.978±0.013	0.824±0.047	0.957±0.021	0.922±0.029	0.972±0.024	0.812±0.043
20	P4_δ	0.012	0.981±0.013	0.839±0.029	0.960±0.020	0.921±0.032	0.975±0.015	0.826±0.044
21	T4_θ	0.011	0.979±0.019	0.853±0.040	0.961±0.025	0.932±0.046	0.982±0.015	0.832±0.057
22	α_f	0.010	0.983±0.018	0.849±0.042	0.958±0.016	0.926±0.015	0.975±0.015	0.828±0.037
23	α_a	0.007	0.979±0.017	0.847±0.043	0.954±0.023	0.921±0.033	0.976±0.018	0.835±0.038
24	F3_{slow}	0.006	0.979±0.017	0.851±0.038	0.967±0.017	0.922±0.033	0.978±0.019	0.833±0.061
25	α_t	0.002	0.981±0.013	0.853±0.037	0.964±0.017	0.910±0.026	0.986±0.012	0.828±0.043

Table A6: The 10-CV score of each classifier when using $\mathrm{Rank}_{\mathrm{RF}}$ as a rank.

No.	$\mathrm{Rank}_{\mathrm{RF}}$	score	SVM	LR	GB	ADA	RF	LDA
1	$\mathrm{F3}_{\delta}$	0.103	0.686±0.068	0.693±0.033	0.669±0.048	0.694±0.026	0.568±0.070	0.690±0.039
2	β_f	0.076	0.767±0.046	0.732±0.039	0.751±0.037	0.747±0.056	0.733±0.037	0.725±0.044
3	$\mathrm{F3}_{\gamma}$	0.066	0.804±0.033	0.729±0.057	0.868±0.037	0.821±0.039	0.883±0.024	0.725±0.051
4	$\mathrm{C3}_{\theta}$	0.052	0.847±0.038	0.701±0.067	0.879±0.043	0.864±0.050	0.885±0.029	0.711±0.058
5	$\mathrm{C3}_{\delta}$	0.048	0.826±0.038	0.719±0.048	0.897±0.021	0.853±0.032	**0.907±0.027**	0.721±0.050
6	$\mathrm{T3}_{\gamma}$	0.045	0.860±0.037	0.724±0.043	**0.904±0.038**	0.865±0.037	0.925±0.024	0.722±0.045
7	$\mathrm{T4}_{\theta}$	0.045	0.872±0.025	0.717±0.031	0.914±0.034	0.868±0.039	0.950±0.023	0.726±0.040
8	$\mathrm{T4}_{\mathrm{Low}\beta}$	0.045	0.890±0.043	0.731±0.057	0.919±0.025	0.894±0.031	0.957±0.017	0.742±0.041
9	$\mathrm{F3}_{\alpha}$	0.041	**0.917±0.030**	0.776±0.039	0.925±0.023	0.896±0.025	0.951±0.042	0.785±0.034
10	$\mathrm{P4}_{\theta}$	0.038	0.949±0.025	0.778±0.025	0.936±0.023	**0.901±0.031**	0.968±0.015	0.788±0.071
11	$\mathrm{F3}_{\theta}$	0.038	0.944±0.019	0.774±0.033	0.935±0.030	0.901±0.032	0.975±0.016	0.786±0.038
12	$\mathrm{F4}_{\delta}$	0.036	0.965±0.023	0.799±0.037	0.951±0.026	0.915±0.039	0.971±0.021	**0.819±0.040**
13	$\mathrm{C3}_{\mathrm{RG}}$	0.036	0.969±0.026	**0.810±0.038**	0.954±0.021	0.921±0.032	0.958±0.014	0.806±0.040
14	$\mathrm{P4}_{\delta}$	0.036	0.969±0.018	0.833±0.059	0.960±0.019	0.919±0.022	0.971±0.024	0.822±0.026
15	$\mathrm{F7}_{\alpha}$	0.035	0.975±0.018	0.836±0.037	0.957±0.024	0.907±0.022	0.974±0.023	0.828±0.028
16	$\mathrm{FP1}_{\delta}$	0.033	0.978±0.015	0.847±0.038	0.953±0.023	0.912±0.036	0.974±0.013	0.825±0.025
17	$\mathrm{F3}_{\beta}$	0.032	0.978±0.011	0.846±0.042	0.958±0.021	0.924±0.027	0.969±0.020	0.828±0.026
18	$\mathrm{P4}_{\alpha}$	0.032	0.976±0.015	0.843±0.033	0.967±0.019	0.925±0.017	0.972±0.022	0.829±0.032
19	$\mathrm{F4}_{\alpha}$	0.029	0.981±0.020	0.839±0.035	0.956±0.016	0.915±0.042	0.972±0.015	0.829±0.035
20	$\mathrm{T6}_{\alpha}$	0.029	0.979±0.019	0.844±0.028	0.957±0.022	0.935±0.016	0.976±0.026	0.831±0.040
21	$\mathrm{F3}_{\mathrm{slow}}$	0.027	0.979±0.014	0.844±0.039	0.969±0.025	0.933±0.023	0.975±0.016	0.825±0.040
22	α_f	0.026	0.979±0.024	0.843±0.022	0.958±0.012	0.931±0.024	0.982±0.013	0.825±0.029
23	α_a	0.023	0.981±0.015	0.847±0.036	0.962±0.023	0.911±0.029	0.975±0.016	0.822±0.034
24	$\mathrm{F3}_{\mathrm{Low}\beta}$	0.019	0.979±0.017	0.844±0.045	0.958±0.028	0.917±0.022	0.969±0.017	0.833±0.060
25	α_t	0.012	0.975±0.014	0.851±0.037	0.957±0.037	0.907±0.044	0.978±0.009	0.831±0.040

Table A7: The 10-CV score of each classifier when using $\mathrm{Rank}_{\mathrm{Ensemble}}$ as a rank.

No.	$\mathrm{Rank}_{\mathrm{Ensemble}}$	score	SVM	LR	GB	ADA	RF	LDA
1	β_f	15	0.693±0.057	0.669±0.046	0.646±0.038	0.671±0.035	0.585±0.042	0.667±0.042
2	$\mathrm{F3}_{\delta}$	18	0.765±0.029	0.731±0.048	0.742±0.050	0.736±0.043	0.733±0.036	0.728±0.038
3	$\mathrm{F4}_{\delta}$	34	0.775±0.057	0.725±0.035	0.761±0.051	0.774±0.032	0.769±0.038	0.726±0.045
4	$\mathrm{F3}_{\beta}$	34	0.849±0.040	0.743±0.047	0.840±0.028	0.817±0.035	0.860±0.037	0.742±0.064
5	$\mathrm{P4}_{\delta}$	45	0.867±0.044	0.728±0.070	0.860±0.058	0.839±0.032	0.879±0.028	0.728±0.067
6	$\mathrm{F3}_{\gamma}$	47	0.899±0.040	0.735±0.033	**0.928±0.025**	0.892±0.034	**0.939±0.037**	0.749±0.052
7	$\mathrm{P4}_{\theta}$	48	0.890±0.040	0.754±0.041	0.940±0.028	**0.908±0.036**	0.947±0.024	0.765±0.036
8	$\mathrm{C3}_{\theta}$	49	**0.925±0.023**	0.782±0.058	0.942±0.029	0.910±0.028	0.956±0.025	0.782±0.035
9	$\mathrm{C3}_{\mathrm{RG}}$	52	0.944±0.030	0.775±0.030	0.946±0.024	0.900±0.031	0.953±0.017	0.785±0.037
10	$\mathrm{T4}_{\theta}$	54	0.947±0.017	0.794±0.050	0.960±0.021	0.917±0.036	0.960±0.024	0.796±0.035
11	$\mathrm{T4}_{\mathrm{Low}\beta}$	54	0.958±0.023	0.797±0.058	0.957±0.024	0.914±0.040	0.969±0.010	**0.801±0.052**
12	$\mathrm{P4}_{\alpha}$	57	0.971±0.020	**0.811±0.060**	0.954±0.019	0.947±0.018	0.975±0.022	0.818±0.038
13	$\mathrm{F7}_{\alpha}$	57	0.975±0.025	0.815±0.050	0.956±0.020	0.937±0.023	0.971±0.017	0.824±0.042
14	$\mathrm{F3}_{\alpha}$	59	0.972±0.025	0.838±0.040	0.956±0.025	0.928±0.017	0.974±0.025	0.833±0.026
15	$\mathrm{F3}_{\theta}$	61	0.976±0.021	0.849±0.034	0.958±0.016	0.926±0.030	0.969±0.016	0.828±0.042
16	$\mathrm{C3}_{\delta}$	61	0.978±0.023	0.849±0.058	0.957±0.025	0.932±0.016	0.975±0.019	0.829±0.037
17	$\mathrm{F4}_{\alpha}$	67	0.978±0.015	0.844±0.056	0.961±0.016	0.925±0.023	0.968±0.015	0.829±0.032
18	$\mathrm{F3}_{\mathrm{Low}\beta}$	69	0.979±0.018	0.849±0.036	0.965±0.024	0.926±0.028	0.974±0.025	0.839±0.043
19	$\mathrm{T3}_{\gamma}$	71	0.981±0.013	0.840±0.035	0.961±0.017	0.925±0.028	0.972±0.025	0.836±0.058
20	$\mathrm{T6}_{\alpha}$	73	0.981±0.015	0.850±0.053	0.961±0.010	0.933±0.036	0.975±0.018	0.836±0.041
21	$\mathrm{FP1}_{\delta}$	79	0.979±0.009	0.844±0.037	0.958±0.027	0.921±0.026	0.974±0.018	0.828±0.049
22	$\mathrm{F3}_{\mathrm{slow}}$	88	0.981±0.013	0.844±0.040	0.953±0.039	0.917±0.039	0.974±0.018	0.829±0.036
23	α_f	94	0.981±0.011	0.854±0.036	0.957±0.017	0.925±0.035	0.969±0.017	0.831±0.027
24	α_a	103	0.979±0.013	0.850±0.038	0.960±0.027	0.922±0.038	0.979±0.013	0.831±0.037
25	α_t	111	0.978±0.015	0.844±0.020	0.968±0.019	0.929±0.030	0.978±0.018	0.832±0.039

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