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 which could lead to depression and anxiety; therefore, a self-diagnosing tool can help notify an individual beforehand. EEG potential has been successful as a mean of prediction human emotion, but studies on EEG and chronic stress are limited. We recorded rest-state EEG and Perceived Stress Scale (PSS) score from 55 participants. Five frequency bands and asymmetry are extracted as features from the rest-state EEG. A feature selection procedure was performed using a t-test and feature importance scores from five classifiers. A RBF-SVM achieved a 10-cv score over 0.9 using eight different frequency bands, electrodes, and asymmetries namely, $\boldsymbol{\beta_f}$, F3$_\delta$, F4$_{\boldsymbol{\delta}}$, F3$_{\boldsymbol{\beta}}$, P4$_{\boldsymbol{\delta}}$, F3$_\gamma$, P4$_{\boldsymbol{\theta}}$, and C3$_{\boldsymbol{\theta}}$. This paper shows the empirical method of feature selection and confirms that EEG can be used in the chronic stress classification.

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) occurrence [1], where acute stress is usually not a health risk, while 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 also affects the human body at different levels ranging from skin conditions, eating habits, 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 around the individual undertake appropriate stress relief therapies.

Several studies that 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 in the past, and they may hide their real feelings due to personal circumstances. As a result, genuine stress may out come to light. 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 [7, 8]. However, the relationship between chronic stress and EEG signals has not been widely investigated.

The aim of this study is to identify which EEG features are important contributors to predictive classification accuracy. We performed a study with a total of 55 participants, whose rest-state EEG measurement were recorded for ten minutes with eyes closed. The label of each participant was calculated from the statistics of their PSS score. An initial 133 features including five EEG frequency bands (δ, θ, α, β, γ), two custom bands (slow, β_{low}), one engineered band (γ_{relative}) from 16 electrodes and five asymmetries of Alpha and Beta band are extracted from the recorded EEG. We selected the 25 most important features using t-test. We ranked the 25 features with six methods. The first five are based on fice classifiers' feature importance scores. The five classifiers are 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 ranked using ranked voting scheme. Finally, 10-CV score is used to verify the rank and t-Distributed Stochastic Neighbor Embedding (t-SNE) is used for visualizing the similarity of Stress and Non-Stress groups given a set of features.

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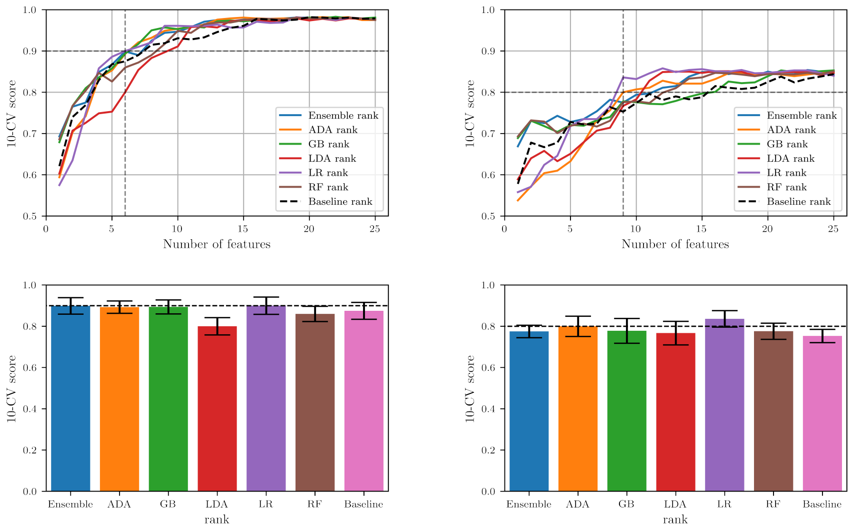
We found that the SVM with Radial Basis Function (RBF) kernel achieves close or up to 0.9 10-CV score when using top six features from Rank_{LR} and $\text{Rank}_{\text{Ensemble}}$ as shown in Figure 1a. Top eight features in $\text{Rank}_{\text{Ensemble}}$ are β_f, F3_δ, F4_δ, F3_β, P4_δ, F3_γ, P4_θ, and C3_θ. In addition, t-SNE seems to suggest

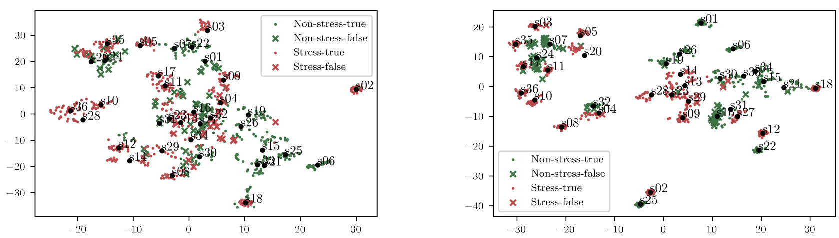
Fig. 1: 10-CV score of both SVM and LR classifier when using different rank at different number of features. A line plot show the trend of 10-CV when increasing the number of feature based on ranks. The bar plot show the 10-CV score at the number of feature, 6 for SVM and 9 for LR.



(a) SVM (b) LR

that top six $\mathrm{Rank}_{\mathrm{Ensemble}}$ are a better representation of a chronic stress when comparing to the $\mathrm{Rank}_{\mathrm{Baseline}}$ as shown in Figure 2.

Fig. 2: The top six features from $\mathrm{Rank}_{\mathrm{Baseline}}$ and $\mathrm{Rank}_{\mathrm{Ensemble}}$ plot in t-SNE space. Color green and red indicate the group Non-stress and Stress respectively and shape dot and x indicates the classification result with rbf-SVM.



(a) Baseline (b) Ensemble

This paper shows the empirical method of feature selection by combining t-test result with coefficient/feature importance score of five different classifiers. Our result confirms that EEG is a viable data for classifying chronic stress and the top eight features agree with the previous work that Delta and Beta are the most important frequency for this task.

2 Related work

Stress is known to cause aberrant reactions in the autonomic nervous system (ANS), which is comprised of the antagonistic regulation of the sympathetic (SNS) as well as the parasympathetic (PNS) nervous system [9, 10]. These two systems are associated with stress and relaxation responses, respectively. Changes in the ANS can be detected by EEG signals [11]. In recent years, EEG signals have become an alternative technique to analyze mental states including stress [7, 8]. EEG signals can be decomposed into frequency band[12], where each of the frequency bands can be utilized to differentiate between different brain states [13]. A changes of power in β band is associated with alertness, whereas θ band occurred throughout the sleep state, and α band rose with relaxation [14]. Recently, some studies used EEG signals conducted with various signals processing and machine learning methods to detect stress.

Several studies have demonstrated the relationship between stress and EEG signals and show that EEG can be used as an input variable in both short-term and long-term stress analysis. In EEG, the α band is commonly used in stress assessment because it is increasing during the relaxation situation. On the other hand, it is decreasing during stress condition [15]. In contrast, α is not the only band that can indicate mental stress. The β band has been found as a sign of mental stress due to an increase of power in β band associated with an increase in alertness when performing cognitive tasks. The relationship between stress and β band at the anterior temporal lobe has demonstrated when stress-inducing pictures were shown [7, 11, 16]. Meanwhile, theta band was used to assess stress during mental arithmetic tasks [17]. Moreover, the relative gamma band has been proposed as a biomarker for the identification of stress [18].

Previous studies have demonstrated the feasibility of using EEG for chronic stress assessment. Chronic stress is measured without involving stress-induced tasks. Since chronic stress is a greater indicator of depressive symptoms than acute stress [5] as well as the potential of EEG to be employed as a stress indicator in everyday life [19]. Thus, we propose the use of EEG signals to identify chronic stress without inducing stress.

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 16 active electrodes, 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 10 - 20 system EEG electrode placement with the sampling rate of 125 Hz. The experimental procedure showed in Figure 3. All participants were initially instructed regarding the experimental procedure and signed consent form. The experiment was carried out after each participant taking the PSS questionnaire. Each participant was placed comfortably in a chair and asked to close their eyes for five minutes while keeping their head motionless to eliminate movement artifacts. The closed-eyes condition was utilized because the particular stimuli can affect the physical, emotional, cognitive, or behavior of an individual. Thus, the eyes closed condition is a better choice without involving stress induction for chronic stress classification. [1, 19, 20].

In this study, PSS-10 questionnaire was used for assessing and labeling to evaluate the stress of each participant. The questionnaire has ten questions, which each question asks about the frequency of stress in the last month. Each question is answered on a scale of 0, which indicate that the incident has never happened, to 4, which indicate that it occurs frequently. All participants were categorized into three groups based on PSS score, as stress, non-stress, and neutral groups. Therefore, a threshold was chosen based on the following equation:

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

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

where μ represent the mean, σ represent standard deviation of the PSS scores, T_u is the upper threshold and T_l is the lower threshold. Any participants with PSS score lower than T_l is in non-stressed group, higher than T_u is in stressed group, and others are in neutral group.

3.3 Feature Extraction

The recorded five-minute rest-state EEG is segmented into 20 smaller records (15 seconds each). For each records, the five EEG frequency bands were obtained using `psd_welch` function from the `mne` library. 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 low beta (13–17 Hz) were computed

Fig. 3: Experimental procedure and data acquisition process

from every electrode. The ratio of gamma to slow bands was used to calculate a Relative Gamma (RG). Moreover, there were five Alpha and Beta asymmetries determined. The following formulae were used to compute the alpha asymmetries:

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

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

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

where α_f, α_t and α_a indicates frontal, temporal, and alpha asymmetries respectively and $\mathrm{channel}_\alpha$ denotes the power spectral density of alpha at each electrode. Beta asymmetry was determined at the frontal and temporal in the same procedure.

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

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

where β_f, and β_t indicates frontal, temporal asymmetries of beta and $\mathrm{channel}_\beta$ denotes the power spectral density of beta at each electrode.

In total, number of extracted features is $(16 \times 8) + 5 = 133$

3.4 Feature Selection

The data is segmented into 15 seconds long (20 samples from each participant) followed by the feature extraction process. The data is then normalized using the following equation;

$$\mathbf{X}' = \frac{\mathbf{X} - \mu}{\sigma} \tag{8}$$

We rank the importance of normalized features using t-test hence, a set of features with $p < .001$. Then, seven ranks are created as follow.

1. $\mathrm{Rank}_{\mathrm{Baseline}}$: listed with no reason.

2. Rank_{LR}: listed according to the Logistic Regression Coefficient.
3. Rank_{LDA}: listed according to the Linear Discriminant Analysis Coefficient.
4. Rank_{ADA}: listed according to the feature importance score of AdaBoost.
5. Rank_{GB}: listed according to the feature importance score of Gradient Boosting.
6. Rank_{RF}: listed according to the feature importance score of Random Forest.
7. $\text{Rank}_{\text{Ensemble}}$: listed according to the ranking score based on the previous five ranks. The score is calculated using Equation 9

$$\text{score}(x) = \sum_{M=m} \text{Rank}_m.\text{index}(x) \tag{9}$$

where M is $\{\text{LR}, \text{LDA}, \text{ADA}, \text{GB}, \text{RF}\}$ and x is the interested feature. The $\text{Rank}_{\text{Ensemble}}$ is sorted in an ascending order, Thus, feature with the lowest score is the most important one.

3.5 Classification

We extract the band power features from EEG signals and fed these to the classifiers. For classification, we have used two classifiers, Support Vector Machine [13, 21] and Logistic Regression [19], which have been demonstrated in previous studies to be the most efficient classifier [13, 19, 22].

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

A total of 55 participants can be divided into 3 groups consisting of Stress, Non-Stress, and Neutral groups based on the PSS questionnaire score. From the Equation 1 and Equation 2, we obtain the μ, σ = (20.75±6.13). The score lower than 17.68 is considered to be Non-Stress group, whereas the score higher than 23.81 is considered to be Stress group. The participants with a score in between the first standard deviation 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

The independent sample t-test with $p < .001$ was used to select feature in this 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 the t-test 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**

There are 25 features with $p < .001$ which are $\mathrm{FP1}_\delta$, $\mathrm{F3}_\delta$, $\mathrm{F4}_\delta$, $\mathrm{C3}_\delta$, $\mathrm{P4}_\delta$, $\mathrm{F3}_\theta$, $\mathrm{C3}_\theta$, $\mathrm{T4}_\theta$, $\mathrm{P4}_\theta$, $\mathrm{F3}_\alpha$, $\mathrm{F4}_\alpha$, $\mathrm{F7}_\alpha$, $\mathrm{T6}_\alpha$, $\mathrm{P4}_\alpha$, $\mathrm{F3}_\beta$, $\mathrm{F3}_\gamma$, $\mathrm{T3}_\gamma$, $\mathrm{F3}_{\mathrm{slow}}$, $\mathrm{F3}_{\mathrm{Low}\beta}$, $\mathrm{T4}_{\mathrm{Low}\beta}$, $\mathrm{C3}_{\mathrm{RG}}$, α_f, α_t, α_a,β_f. We use this as a list for $\mathrm{Rank}_{\mathrm{Baseline}}$.

4.3 Ranking with coefficient and feature importance score

We rank the 25 features from the t-test result using coefficient/feature importance score of a classifier as mentioned in the Section 3.4. To verify any Rank_m where $m \in \{\mathrm{LR}, \mathrm{LDA}, \mathrm{ADA}, \mathrm{GB}, \mathrm{RF}\}$, we (1) iterate over the index of Rank_m; (2) select the features from the Rank_m^1 to Rank_m^i where i is the current iteration; (3) calculate the 10-CV score using rbf-SVM and LR; and (4) plot the t-SNE space to visualize the similarity of samples given the features from the iteration that SVM can achieve over 0.9 10-CV score.

The 10-CV score threshold of 0.9 for SVM and 0.8 for LR is selected based on the 10-CV score of each model when training the model using 25 features. The SVM exceeds 0.9 10-CV score while LR can reach 0.85 at best. Table that reports every ranks and 10-CV score of all classifiers can be found in Appendix A.

4.3.1 Baseline

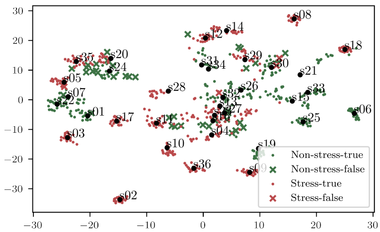
When using $\mathrm{Rank}_{\mathrm{Baseline}}$, rbf-SVM can achieve 0.9 10-CV score with top eight features including $\mathrm{FP1}_\delta$, $\mathrm{F3}_\delta$, $\mathrm{F4}_\delta$, $\mathrm{C3}_\delta$, $\mathrm{P4}_\delta$, $\mathrm{F3}_\theta$, $\mathrm{C3}_\theta$, and $\mathrm{T4}_\theta$ as shown in

Table 3. Using the same rank with LR, however, the model requires top 16 features in order to reach 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 where i is the row number.

No.	$\text{Rank}_{\text{Baseline}}$	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. 4: 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

Table 4 shows the result using the ranked features of Logistic Regression Coefficient. With this rank, the SVM is able to achieve 0.9 10-CV score at top six features. The LR classifier also reach 0.8 10-CV score at top nine features, seven features less than the $\text{Rank}_{\text{Baseline}}$. The top six features of Rank_{LR} are $F3_\beta$, $P4_\delta$, β_f, $C3_{RG}$, $F3_\delta$, $F4_\delta$, and $T4_\theta$.

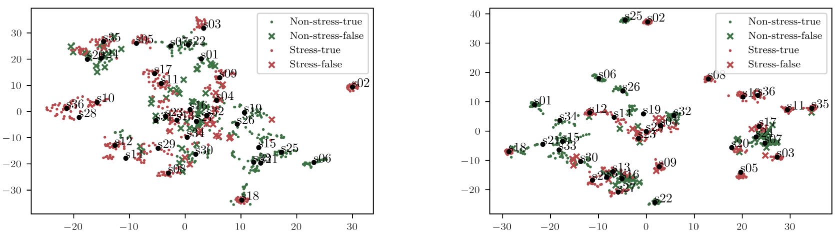
Table 4: The 10-CV score of each classifier when using Rank_{LR} as a rank. The model is trained on a list of features from Rank^1 to Rank^i where i is the row number.

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	$C3_{RG}$	-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

4.3.3 Ensemble

The score for $\text{Rank}_{\text{Ensemble}}$ is calculated follow the Equation 9. Table 5 shows the calculated score and rank them accordingly. In this configuration, SVM, at top six features, 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 $C3_\theta$.

Fig. 5: 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}.



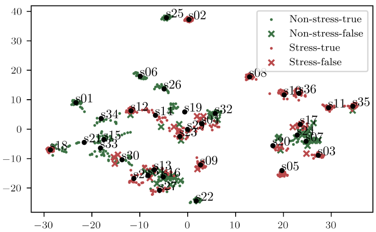
(a) Baseline

(b) LR

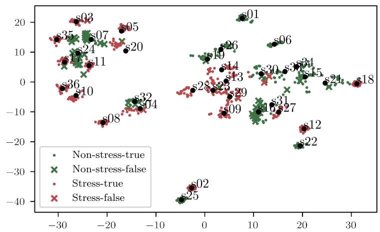
Table 5: The 10-CV score of each classifier when using $\text{Rank}_{\text{ensemble}}$ as a rank. The model is trained on a list of features from Rank^1 to Rank^i where i is the row number.

No.	$\text{Rank}_{\text{ensemble}}$	score	SVM	LR
1	β_f	15	0.693±0.057	0.669±0.046
2	F3_δ	18	0.765±0.029	0.731±0.048
3	F4_δ	34	0.775±0.057	0.725±0.035
4	F3_β	34	0.849±0.040	0.743±0.047
5	P4_δ	45	0.867±0.044	0.728±0.070
6	F3_γ	47	0.899±0.040	0.735±0.033
7	P4_θ	48	0.890±0.040	0.754±0.041
8	C3_θ	49	**0.925±0.023**	0.782±0.058
9	C3_{RG}	52	0.944±0.030	0.775±0.030
10	T4_θ	54	0.947±0.017	0.794±0.050
11	$\text{T4}_{\text{Low}\beta}$	54	0.958±0.023	0.797±0.058
12	P4_α	57	0.971±0.020	**0.811±0.060**
13	F7_α	57	0.975±0.025	0.815±0.050
14	F3_α	59	0.972±0.025	0.838±0.040
15	F3_θ	61	0.976±0.021	0.849±0.034
16	C3_δ	61	0.978±0.023	0.849±0.058
17	F4_α	67	0.978±0.015	0.844±0.056
18	$\text{F3}_{\text{Low}\beta}$	69	0.979±0.018	0.849±0.036
19	T3_γ	71	0.981±0.013	0.840±0.035
20	T6_α	73	0.981±0.015	0.850±0.053
21	FP1_δ	79	0.979±0.009	0.844±0.037
22	F3_{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

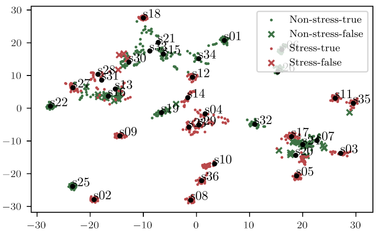
Fig. 6: The top six and top eight features from $\mathrm{Rank}_{\mathrm{LR}}$ and $\mathrm{Rank}_{\mathrm{Ensemble}}$ plot in t-SNE space.



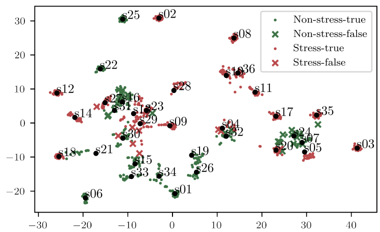
(a) top six LR



(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 5. 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 [19]

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 $\mathrm{Rank}_{\mathrm{Ensemble}}$ shows the top eight Chronic Stress features which are β_f, $\mathrm{F3}_\delta$, $\mathrm{F4}_\delta$, $\mathrm{F3}_\beta$, $\mathrm{P4}_\delta$, $\mathrm{F3}_\gamma$, $\mathrm{P4}_\theta$, and $\mathrm{C3}_\theta$. With these eight features, rbf-SVM, ADA, GB, and RF achieve over 0.9 10-CV score while adding the next four features ($\mathrm{C3}_{\mathrm{RG}}$, $\mathrm{T4}_\theta$, $\mathrm{T4}_{\mathrm{Low}\beta}$, and $\mathrm{P4}_\alpha$), 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.

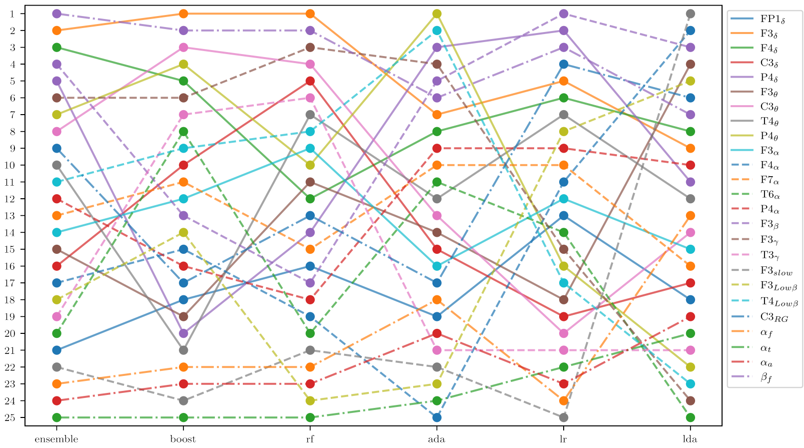


Table A1: The 10-CV score of each classifier when using Rank$_{\text{baseline}}$ as a rank.

No.	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	$F3_\beta$	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	$P4_\delta$	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	$C3_{\mathrm{RG}}$	-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	$F3_\delta$	-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	$F4_\delta$	-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	$T4_\theta$	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	$F3_{\mathrm{Low}\beta}$	-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	$P4_\alpha$	-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	$F7_\alpha$	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	$F4_\alpha$	-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	$F3_\alpha$	-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	$FP1_\delta$	-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	$T6_\alpha$	-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	$F3_\gamma$	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	$P4_\theta$	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	$T4_{\mathrm{Low}\beta}$	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	$F3_\theta$	-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	$C3_\delta$	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	$C3_\theta$	-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	$T3_\gamma$	-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	$F3_{\mathrm{slow}}$	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	$F3_{\mathrm{slow}}$	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	$F4_\alpha$	-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	$F3_\beta$	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	$F3_\theta$	-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	$F3_{\mathrm{Low}\beta}$	-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	$C3_{\mathrm{RG}}$	-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	$F4_\delta$	-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	$F3_\delta$	-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	$P4_\alpha$	-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	$P4_\delta$	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	$T4_\theta$	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	$C3_\theta$	-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	$F3_\alpha$	-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	$F7_\alpha$	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	$C3_\delta$	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	$FP1_\delta$	-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	$T3_\gamma$	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	$P4_\theta$	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	$T4_{\mathrm{Low}\beta}$	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	$F3_\gamma$	-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	$T6_\alpha$	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 $\mathrm{Rank}_{\mathrm{ADA}}$ as a rank.

No.	$\mathrm{Rank}_{\mathrm{ADA}}$	score	SVM	LR	GB	ADA	RF	LDA
1	$P4_{\theta}$	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	$T4_{\mathrm{Low}\beta}$	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	$P4_{\delta}$	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	$F3_{\gamma}$	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	$F3_{\beta}$	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	$F3_{\delta}$	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	$F4_{\delta}$	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	$P4_{\alpha}$	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	$F7_{\alpha}$	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	$T6_{\alpha}$	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	$T4_{\theta}$	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	$C3_{\theta}$	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	$F3_{\theta}$	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	$C3_{\delta}$	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	$F3_{\alpha}$	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	$C3_{\mathrm{RG}}$	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	$FP1_{\delta}$	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	$T3_{\gamma}$	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	$F3_{\mathrm{slow}}$	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	$F3_{\mathrm{Low}\beta}$	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	$F4_{\alpha}$	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 $\mathrm{Rank}_{\mathrm{GB}}$ as a rank.

No.	$\mathrm{Rank}_{\mathrm{GB}}$	score	SVM	LR	GB	ADA	RF	LDA
1	$F3_{\delta}$	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	$C3_{\theta}$	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	$P4_{\theta}$	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	$F4_{\delta}$	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	$F3_{\gamma}$	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	$T3_{\gamma}$	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	$T6_{\alpha}$	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	$T4_{\mathrm{Low}\beta}$	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	$C3_{\delta}$	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	$F7_{\alpha}$	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	$F3_{\alpha}$	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	$F3_{\beta}$	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	$F3_{\mathrm{Low}\beta}$	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	$F4_{\alpha}$	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	$P4_{\alpha}$	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	$C3_{\mathrm{RG}}$	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	$FP1_{\delta}$	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	$F3_{\theta}$	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	$P4_{\delta}$	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	$T4_{\theta}$	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	$F3_{\mathrm{slow}}$	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 $\mathrm{Rank_{RF}}$ as a rank.

No.	$\mathrm{Rank_{RF}}$	score	SVM	LR	GB	ADA	RF	LDA
1	$F3_\delta$	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	$F3_\gamma$	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	$C3_\theta$	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	$C3_\delta$	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	$T3_\gamma$	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	$T4_\theta$	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	$T4_{\mathrm{Low}\beta}$	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	$F3_\alpha$	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	$P4_\theta$	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	$F3_\theta$	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	$F4_\delta$	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	$C3_{\mathrm{RG}}$	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	$P4_\delta$	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	$F7_\alpha$	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	$FP1_\delta$	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	$F3_\beta$	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	$P4_\alpha$	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	$F4_\alpha$	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	$T6_\alpha$	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	$F3_{\mathrm{slow}}$	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	$F3_{\mathrm{Low}\beta}$	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 $\mathrm{Rank_{Ensemble}}$ as a rank.

No.	$\mathrm{Rank_{Ensemble}}$	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	$F3_\delta$	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	$F4_\delta$	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	$F3_\beta$	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	$P4_\delta$	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	$F3_\gamma$	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	$P4_\theta$	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	$C3_\theta$	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	$C3_{\mathrm{RG}}$	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	$T4_\theta$	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	$T4_{\mathrm{Low}\beta}$	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	$P4_\alpha$	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	$F7_\alpha$	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	$F3_\alpha$	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	$F3_\theta$	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	$C3_\delta$	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	$F4_\alpha$	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	$F3_{\mathrm{Low}\beta}$	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	$T3_\gamma$	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	$T6_\alpha$	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	$FP1_\delta$	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	$F3_{\mathrm{slow}}$	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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