Wearable EEG-Based Cognitive Load Classification by Personalized and Generalized Model Using Brain Asymmetry

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Abstract: EEG measures have become prominent with the increasing popularity of non-invasive, portable EEG sensors for neuro-physiological measures to assess cognitive load. In this paper, utilizing a four-channel wearable EEG device, the brain activity data from eleven participants were recorded while watching a relaxation video and performing three cognitive load tasks. The data was pre-processed using outlier rejection based on a movement filter, spectral filtering, common average referencing, and normalization. Four frequency-domain feature sets were extracted from 30-second windows encompassing the power of δ, θ, α, β and γ frequency bands, the respective ratios, and the asymmetry features of each band. A personalized and generalized model was built for the binary classification between the relaxation and cognitive load tasks and self-reported labels. The asymmetry feature set outperformed the band ratio feature sets with a mean classification accuracy of 81.7% for the personalized model and 78% for the generalized model. A similar result for the models from the self-reported labels necessitates utilizing asymmetry features for cognitive load classification. Extracting high-level features from asymmetry features in the future may surpass the performance. Moreover, the better performance of the personalized model leads to future work to update pre-trained generalized models on personal data.

1 INTRODUCTION

Cognitive load is a term from cognitive psychology which refers to the amount of working memory used in the brain. The ratio of the occupied processing capability of the working memory and the amount required by the task can be referred to as cognitive workload (Hart and Staveland, 1988). Therefore, identifying a potential cognitive overload is essential, especially for professionals such as drivers, pilots, medical professionals, emergency workers, and air traffic control. Furthermore, systems with the ability to adapt to the user's cognitive state could improve work performance and help avoid mistakes.

Additionally, complex cognitive tasks alone or combined with other factors like time or social pressure can release cortisol resulting in psychological stress (Reinhardt et al., 2012). Stress can build up to long-term stress, leading to high blood pressure, anxiety, anger, helplessness, and reduced resilience (Marschall, 2020). Moreover, some patients suffering from epilepsy report stress as premonitory symptoms or seizure trigger way before the seizure occurs (Moontaha et al., 2020). Across disciplines, researchers are actively working on providing objective measurement techniques to monitor, predict or detect stress-related events with the ultimate goal of providing pre-emptive therapy for these diseases.

For the subjective ratings of the cognitive load, the Nasa Task Load Index (Nasa-TLX) (Hart and Staveland, 1988) is widely used in the literature, and so is in this work. For the objective load measure, the data-driven neuro-physiological measures are mostly skin conductance (Setz et al., 2010), anterior cingulate cortex signal, blood volume pulse, temperature, and magnetoencephalography (Chen et al., 2016). The growing popularity of wearable devices measuring galvanic skin response (GSR), eye activity, respiration, and electrocardiography activity (ECG) has become increasingly prominent for less obtrusive online assessment of cognitive load (Verwey andVeltman, 1984; Boucsein, 1992). The review on the mental state classification provides extensive information on

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the multi-modality used in this domain (Anders and Arnrich, 2022).

In the past two decades, the measurement of mental states with neuro-physiological activity, particularly EEG measurements, has become quite popular. One reason being EEG measures electrical correlates directly from the brain rather than the indirect measurement of other physiological responses initiated by the brain. Since 1998 (Gevins et al., 1998) until today (Asif et al., 2019), several publications have shown that EEG is a viable source of information regarding a person's cognitive load, by achieving classification accuracy of up to 95%. However, these results are highly dependent on the different number of EEG channels used, the amount of train and test data for machine learning (ML), the length and nature of the tasks performed, time-domain or frequency-domain features, and personalized or generalized models (Grimes et al., 2008). Most importantly, very few of the existing experimental paradigms for cognitive load assessment utilize wearable EEG with four channels or less (Katmah et al., 2021), (Ahn et al., 2019), (Fangmeng et al., 2020). Additionally, when it comes to the dry electrode measurement, even fewer studies have been found for cognitive load assessment (Arpaia et al., 2020). Another study using four electrodes to classify stress is limited to detecting perceived stress rather than instantaneous stress (Arsalan et al., 2019). Therefore, one of the novelties of this paper is to use a low-cost wearable device with only four dry electrodes to assess cognitive load in a controlled environment. Eventually, this will help as a baseline to monitor the user's cognitive performance in daily life scenarios.

To detect cognitive load from EEG data, the extraction of spectral components is well-known in the literature (Ismail and Karwowski, 2020; Longo et al., 2022). Primarily, band powers from *delta* (0.5-4Hz), *theta* (4-7Hz), *alpha* (8-12Hz), *beta* (12-30Hz) and *gamma* (30-50Hz) frequency components are extracted. As such, a promising correlation has been found between mental fatigue and the power ratio features from the different band powers (Borghini et al., 2014). Theta and alpha features are well-established features for cognitive load measurement (Antonenko et al., 2010). The authors found a correlation between cognitive load and the alpha-to-theta ratios and theta-to-alpha ratios by applying machine learning methods (Raufi and Longo, 2022). Frontal alpha asymmetry (Barros et al., 2022) (Sun et al., 2017) along with the asymmetry between each frequency band (Ahn et al., 2019) are also significantly related to the cognitive load. However, the related work is limited to either stationary EEG setups and insufficient amounts of different cognitive load tasks (Kutafina et al., 2021), or fails to investigate on ML algorithms (Negi and Mitra, 2018).

The performance of ML classifiers depends on the training paradigm and other factors. Using 24 channels of EEG, (Pang et al., 2021) achieved 75.9% of classification accuracy for personalized models while with clinical grade EEG, (Jiménez-Guarneros and Gómez-Gil, 2017) achieved 91% of classification accuracy by developing a generalized model. Another publication also used a personalized model to estimate cognitive load across affective contexts (Mühl et al., 2014) with different classifiers using different time- and frequency-domain features.

In summary, the contributions of this paper to the study of cognitive load are:

- The evaluation of cognitive load classifier using wearable EEG devices with four channels of dry electrodes to be transferable to daily life cognitive load measurement.
- Feature extraction and exploration from θ_α, θ_α_ratio, and asymmetry features, providing that the classification performance is higher with the asymmetry features.
- The comparison of personalized models with generalized models for different feature sets to state-of-the-art.
- The correlation between self-report and physiological data by evaluating personalized and generalized models based on self-reported labels.

The following sections provide an overview of the study protocol, the classification results, and the conclusions of the findings of this paper.

2 MATERIALS AND METHODS

In this paper, an experiment was designed to induce cognitive load to participants. This section discusses the materials and methods used in building and evaluating this experiment.

2.1 Materials

Data Acquisition: The local ethics committee from the University of Potsdam approved the experimental paradigm. Eleven participants (six male and five female) were recruited for cognitive load measurements. Participants were university students with Asian or European backgrounds (24 to 34 years, mean of 28.1 years) and were fluent in either English or German. To collect EEG data we used the *Muse*

S [1] headband together with the *Mind-monitor*[2] application. The Muse S headband is an unobtrusive consumer-grade device with four channels *TP9, AF7, AF8,* and *TP10* following the international 10-20 system. While Mind-monitor already offers some signal processing, we used the four raw EEG signals and the acceleration data for each axis. The data was collected at the sampling frequency of 256Hz.

Psychopy: We built the experiment in Psychopy (Peirce et al., 2022) to show the cognitive load stimuli, extract the Nasa-TLX questionnaire scores, and record the timestamps of the start and end of every step of the experiment. This time tracking allows us to label the recorded sensor data later. The Psychopy was developed in the builder view for this experiment.

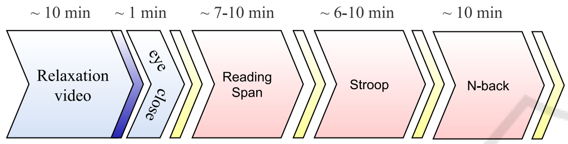


Figure 1: The study protocol followed in this paper. The three tasks: Reading Span, Stroop, and N-back, were self-paced. The time range is mentioned above each block. The yellow bar represents the Nasa-TLX questionnaire. The dark blue bar represents audio data and another questionnaire which are not relevant for this paper.

Study Protocol: Figure 1 shows the study protocol in detail. We welcomed the participants in a quiet room with no external interference. Only one experimenter was present during the experiment sitting on the opposite side of the participant with no visibility of the participant's screen. At the beginning of the experiment, the participants were asked to sign an informed consent. Then, we briefed the participant about the tasks, how to handle the devices, and the Psychopy platform. The participants' comfort with the study environment, e.g., room temperature, seat height, and computer volume, was ensured. Afterward, we showed the participant a relaxation video for 10 minutes to record each individual's baseline. The participants then closed their eyes and relaxed for 1 minute, which provided a baseline phase to use as a reference to analyze changes in the EEG signal when the subject is communicating with the environment, i.e., subtracting the mean of the baseline from the raw signal. Next, the participants were asked by us to perform the cognitive tasks described below:

[1]https://choosemuse.com/muse-s/
[2]https://mind-monitor.com/

Reading Span (RS) Task: In the RS task (**Task1**) (Stone and Towse, 2015), the participant needed to read the sentence aloud and answer logical questions about that task. The participant must remember the numbers between the reading task and enter the previously read three numbers when asked in between the reading task.

Stroop Task: In Stroop Task (**Task2**) (Stroop, 1935), the participant reads a list of words for colors, but the words are printed in colors different from the word itself. For example, the word "orange" would be listed as text but printed in "green". The participant's reading time of the words on the list is then recorded. Next, the participant will repeat the test with a new list of words and name the colors that the words are printed. So, when the word "orange" is printed in green, the participant should say "green" and move on to the next word.

N-back Task: In the N-back task (**Task3**) (Kane and Engle, 2002), participants are presented with two stimuli, one audio and one visual. Participants need to match the stimulus n trials before. For example, in a 2-back task, in the audio stimuli, participants have to decide whether the current audio letter is the same as the letter in trial n–2. In the visual stimuli, participants have to determine whether the current visual box is in the same position as in trial n–2.

Nasa-TLX: In between the three tasks mentioned, we prompted the Nasa-TLX questionnaire. The questionnaire consists of six questions about a previously finished task to capture the self-assessment of the task's mental, physical, and temporal demands and the overall performance, needed effort, and frustration level. The participants answered each question on a visual scale ranging from *"very low"* to *"very high,"* which corresponds to 0 and 100, respectively. Afterward, the participants are asked to weigh each dimension pairwise, allowing the computation of a weighted score of the previously answered question. We saved the individual answers of the different dimensions as floating-point values between 0 and 100 with their corresponding weights. The weighted scores and the corresponding mean score is depicted in table 1

2.2 Methods

The methods followed in the paper are depicted in the figure 2 and explained as follows.

Table 1: Scores from the Nasa-TLX questionnaire (scale from 0 to 100) for the subjective cognitive load indicated by each participant. The right-most column indicates mean score across the three tasks.

Participant ID	Task1	Task2	Task3	mean
1	68.47	70.8	50.9	63.39
2	71.5	40.17	86.43	66.03
3	77.47	77.33	84.87	79.89
4	35.67	40.23	38.37	38.09
5	76.5	86.93	81.4	81.61
6	86.2	33.37	58.57	59.38
7	45.37	51.3	67.53	54.73
8	66.17	48.0	47.03	53.73
9	49.4	62.27	70.7	60.79
10	46.97	45.0	45.87	45.94
11	73.4	39.8	65.5	59.57

Filtering: The recorded EEG signals contain physiological artifacts, e.g., eye blinks, eye movements, head movements, and heartbeats. These raw signals also contain non-physiological artifacts, e.g., power line interference, electrode artifacts due to poor electrode placement, and more. Activation of muscles on the scalp creates high-frequency noise. Additionally, disturbances like heart activity and the slow change of electric conductivity of the skin caused by sweating can create low-frequency noise. Therefore, we applied a low pass Butterworth filter of the sixth order at 50 Hz to remove higher-frequency noise and a high pass filter at 0.5 Hz to remove low-frequency noises.

Movement Filter: To detect and remove the additional head movement, we used a movement filter using the acceleration data recorded via Muse S to detect and remove additional noise from the head movement. At first, we applied a high pass filter at 0.5 Hz and a low pass filter at 20 Hz to remove noise and the gravitational component of the acceleration signal. We calculated the overall movement as the square root of the sum of the squared acceleration magnitudes:

$$movement = \sqrt{Acc_X^2 + Acc_Y^2 + Acc_Z^2}.$$

Then, by visually analyzing the data, we set a fixed threshold at $20\frac{m}{s^2}$ to remove EEG artifacts due to high (unwanted) acceleration. When the acceleration data exceeds the given threshold, we interpolated the EEG data with the average of the previous and next values of the given data points.

Normalization: While general patterns of the different features are shared among the participants, the exact values usually differ for everyone. Therefore, we performed two steps of normalization. Firstly, for *baseline normalization*, we use the one-minute eye closing session as a baseline measurement. We calculated the mean of every feature for this period as a baseline value and subtracted it from the whole recording for every participant. Secondly, *min-max feature scaling* is used by subtracting the minimum from each feature and dividing by the range of each feature all the values:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}.$$

Common Average Referencing: The EEG data was average-referenced after filtering, i.e., the overall average potential is subtracted from each channel. This method relies on the statistical assumption that multichannel EEG recording is uncorrelated and assumes an even potential distribution across the scalp.

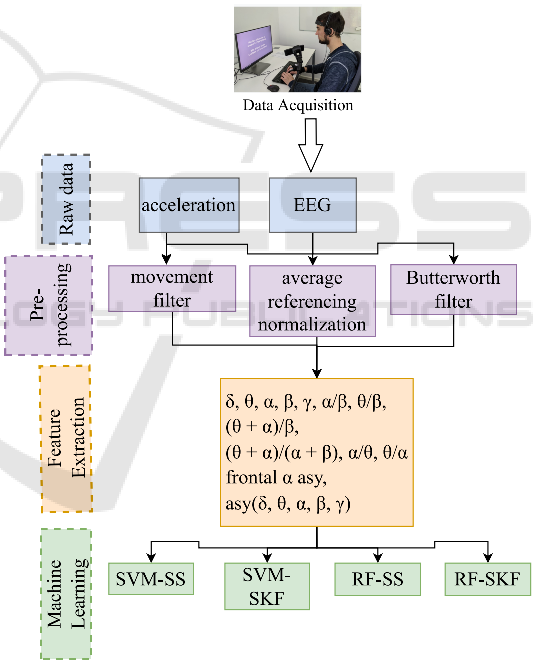


Figure 2: The data analysis framework followed in this paper.

Feature Extraction: We segmented the preprocessed data into 30-second windows with 80% overlap to extract spectral features. Using Welch's method and Hann window function, the power spectral density (PSD) of the five frequency band was calculated for each of the four channels. The mean across the four channels was extracted and named as δ, θ, α, β and γ features. Additionally, we have also calculated the ratio of the band powers of α/β, θ/β, $(\theta+\alpha)/\beta$, $(\theta+\alpha)/(\beta+\alpha)$ from the mean PSD across the electrodes (Barua et al., 2020). These ratios were used for detecting fatigue since an increase in the ratio is a good indicator of EEG activity compared to individual PSDs (Jap et al., 2009). Additionally, θ/α and α/θ ratios were also extracted since these two band ratios are proven as indexes of mental workload (Raufi and Longo, 2022). Finally, α power of EEG electrodes AF8 and AF7 was log-transformed, and the asymmetry score of frontal alpha was calculated by subtracting the value at AF8 from the value at AF7 (log-transformed spectral power at AF8 — log-transformed spectral power at AF7) (Sun et al., 2019). The correlation between the psychological stress and frontal EEG asymmetry is an ongoing promising study (Arpaia et al., 2020). We have also calculated the left and right hemisphere asymmetry of the brain of the five band power (log-transformed spectral power of left hemisphere — log-transformed spectral power of right hemisphere) (Ahn et al., 2019). The definition of the features is summarized in table 2.

Table 2: Feature names and the description of the extracted features from EEG power bands.

Feature name	Description
θ_α	PSD of θ, α
θ_α_ratio	PSD of θ/α, α/θ
asy	asymmetry of frontal α, δ, θ, α, β, γ
all	PSD of δ, θ, α, β and γ, θ_α, θ_α_ratio, asy

2.3 Classifier Models

In this paper, we have built a binary classification models using each feature set mentioned in table 2 to classify between the relaxation baseline and each of the three cognitive load tasks mentioned above. We implemented a Support Vector Machine (SVM) and a Random Forest (RF) classifier in Python using *sklearn*[3]. SVM was selected as the most widely used classifier for mental state detection (Anders and Arnrich, 2022), whereas Decision trees, e.g., the RF model was selected with better interpretability and faster. For both classifiers, we used nested Stratified K-fold cross-validation (SKF) with $K = 8$ and Shuffle Split (SS) cross-validation with 9-splits and test size of 0.25. Using the four classifiers named as svm-skf, rf-skf, svm-ss, and rf-ss we developed personalized and generalized model.

Therefore, for personalized model, in each iteration of the SKF, the data of one participant is divided into 8-folds, where one fold is used for the test and the rest of them for the train. The train set is again divided into 8-folds, where one fold is the validation, and the other is for the train set. For the SS, the data from one participant is randomly sampled during 9 iterations to generate test set of 25% of the data of one participant. The remaining data is again randomly sampled to generate the validation set of the 25% of the remaining data set and rest for the training. For generalized models, data from all participant was taken into account while diving into 8-folds and sampling into test for SKF and SS, respectively.

For both, personalized and generalized models, we tuned the hyper-parameters of the models to avoid over-fitting. Using *sklearn's* GridSearchCV method, we defined a grid of hyper-parameter ranges, randomly sampled from the grid, and performed cross-validation with each combination of values.
For SVM we tuned the Linear kernel with multiple value of the regularization strength C (0.01, 0.05, 0.1, 0.5, 1, 10, 100, 1000). For the Radial bias kernel (RBF), we also tuned the γ kernel coefficient and the regularization parameter C. The parameters were chosen differently for each fold of the iteration for each participant.

For the tree-based RF classifier, we adjusted the number of trees (n_estimators = 50, 100, 200, 400, 800), minimum number of data points allowed in a leaf node (min_samples_leaf = 1, 2, 3, 4, 5, 6), min number of data points placed in a node before the node is split (min_samples_split = 2, 4, 6, 8).

In order to evaluate the classification tasks, we used the accuracy of the prediction, which is the number of correctly predicted samples $\hat{y}_{true}$ divided by the number of all samples $\hat{y}_{total}$:

$$accuracy = \frac{\hat{y}_{true}}{\hat{y}_{total}}.$$

We calculated the mean accuracy over all the folds for each participant for the personalized model and displayed only the mean accuracy over all participant. For generalized model, we showed the mean accuracy over all the folds.

3 RESULTS

3.1 Feature Exploration

At the beginning of the data analysis, as depicted in figure 3, we performed feature exploration by calculating the logarithm of the ratio of α band power (α_log_ratio) and the negative logarithm of the ratio of θ band power (θ_log_ratio) of the baseline relaxation

[3]https://scikit-learn.org/stable/

session to each of the three cognitive load sessions mentioned in figure 1. Due to the different lengths of the relaxation and cognitive load sessions for shorter sessions, we trimmed the starting of the corresponding sessions because the data points toward the end are more relevant for mental state detection from the self-reported labels. Figure 3 shows a total of eleven participants' θ_log_ratio (left) and α_log_ratio (right) with the corresponding tasks in different colors. Out of the 33 sessions across all participants, the positive θ_log_ratio and α_log_ratio for 21 and 25 sessions, respectively, indicates an increase in θ activity and a decrease in α activity with increasing cognitive load. These findings are completely aligned with the findings of the neuroscience literature. The visualization of the α of all the cognitive load sessions consecutively across all participants in figure 4 explains the negative α_log_ratio of participant 4 and participant 5. The shorter time window to finish the tasks and self-report (see table 1) interprets that the designed tasks were too easy for participant 4 to perform, and too difficult for participant 5 to give up. Nevertheless, further investigation is needed for the justification of the negative α_log_ratio for participant 6.

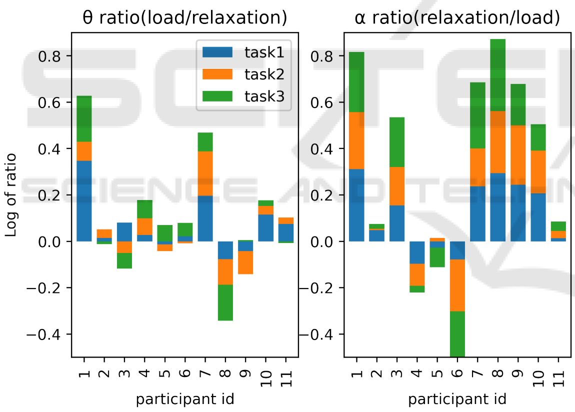


Figure 3: *Left:* logarithm of the ratio of α band power (α_log_ratio) and *right:* negative logarithm of the ratio of θ band power (θ_log_ratio) of the baseline relaxation session to each of the three cognitive load sessions is plotted in the y-axis, whereas x-axis represents each participant. The color bar represents each task. The positive θ_log_ratio and α_log_ratio depicts the increase of θ activity and decrease of α activity with the increased cognitive load, respectively.

Figure 5 demonstrates the distribution of the asymmetry features of the baseline relaxation session and the all cognitive load session together. The mean asymmetry score for the relaxation session is higher by 0.02 than the cognitive load sessions indicating that the right alpha power was reduced than the left alpha power under the load condition. The finding is consistent with the physiological assumptions. However, no statistically significant difference was found between the scores may be due to the imbalanced data. Nevertheless, as mentioned in the following sections, the asymmetry features greatly contribute to the machine learning model.

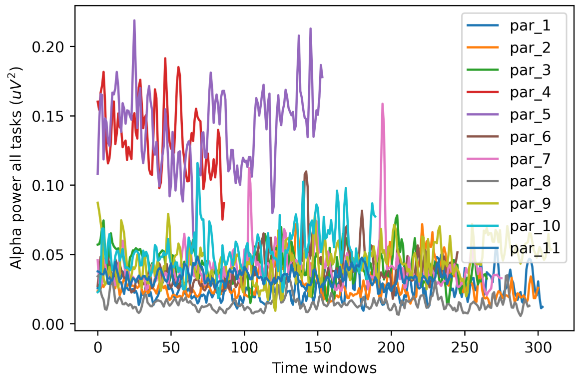


Figure 4: Alpha power for all participants for all three tasks consecutively. Participant 4 and participant 5 took shorter time window to finish the tasks and exhibits higher alpha power compared to other participants.

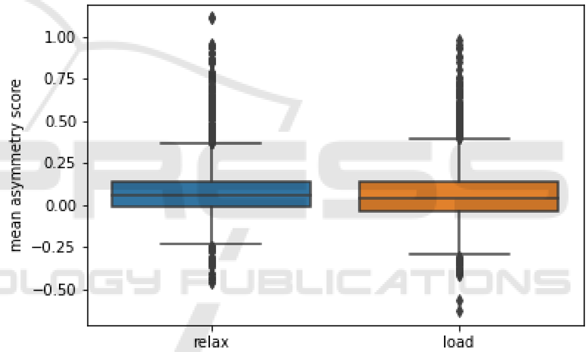


Figure 5: Mean score of the asymmetry features is plotted in the y-axis whereas the x-axis indicates the relaxation baseline session and the cognitive load sessions. The average of the mean asymmetry score is 0.08 for relaxation session and 0.06 for cognitive load session.

3.2 Personalized Model

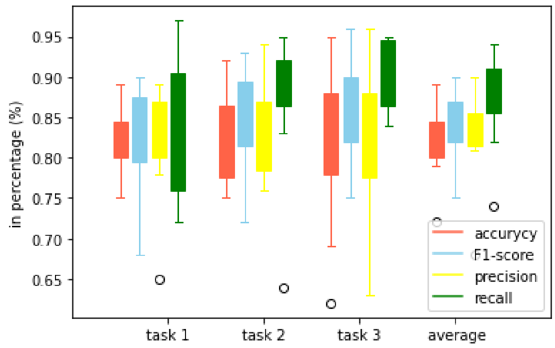
Based on the personalized variations of the extracted features, so do other brain dynamics and the self-rating of cognitive load, the first experimental evaluation was performed on the personalized model for the binary classification between relaxation baseline and each of the cognitive tasks. For every participant, we applied four different feature sets to SVM and RF classifiers with both SKF cross-validation with 8-folds and SS cross-validation with 9-splits and test size of 0.25. The results depicted in table 3 shows that for each feature set the SVM classifier with SS cross-validation performed the best (marked in bold) among each set of four classifiers. The asymmetry feature set outperforms the θ_α and the θ_α_ratio feature sets by achieving the the best mean classification accuracy of 82% for both task1 and task2, and 81% for task3, respectively. However, the accuracy increased by 9%, 7%, and 10% for task1, task2, and task3, respectively, while using all the feature set. The distribution of test accuracy (red), f1_score (blue), precision (yellow), and recall (green) over all participants for the best model, SVM-SS is shown in figure 6 for both asymmetry features 8a and all the features 8b. Each block represents each task, and also the rightmost block represents the average.

Table 3: The mean accuracy over all participant results from a personalized model for each cognitive load task with respect to the relaxation baseline for SVM and RF using four feature sets with both the SKF and SS cross-validation.

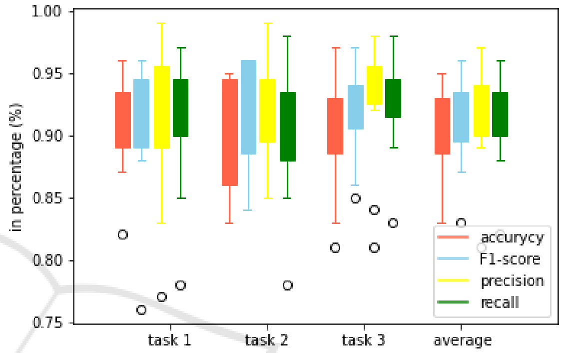
Features	**Classifier -cv**	**task1**	**task2**	**task3**
all	rf-skf	0.87	0.84	0.84
	rf-ss	0.90	0.86	0.88
	svm-skf	0.88	0.84	0.85
	svm-ss	**0.91**	**0.89**	**0.91**
θ_α	rf-skf	0.75	0.72	0.75
	rf-ss	0.76	0.73	0.76
	svm-skf	0.78	0.73	0.75
	svm-ss	**0.8**	**0.73**	**0.76**
θ_α_ratio	rf-skf	0.7	0.67	0.66
	rf-ss	0.73	0.67	0.66
	svm-skf	-	-	-
	svm-ss	**0.75**	**0.69**	**0.69**
asy	rf-skf	0.78	0.77	0.74
	rf-ss	0.82	0.81	0.8
	svm-skf	0.79	0.78	0.76
	svm-ss	**0.82**	**0.82**	**0.81**

3.3 Generalized Model

The second experimental evaluation was performed to develop a generalized model by applying mentioned feature sets in table 2 to create a generalized model using SKF cross-validation with 8-folds and SS cross-validation with 9-splits and a test size of 0.25 for both SVM and RF classifiers for all participants. Figure 7 provides the average accuracy over the three tasks for all the models which were generated with the respective cross-validation. Since figure 7 shows that there is no significant difference between the performance of the RF-SS and SVM-SS classifier, to maintain the homogeneity with the personalized model we report the results from SVM-SS classifier to show the comparison between the test accuracy, f1_score, precision and recall of using asymmetry features and all the features in table 4. As indicated, the asymmetry features surpass both the the θ_α and the θ_α_ratio feature with



(a) asymmetry features



(b) all features

Figure 6: The distribution of test accuracy (red), f1_score (blue), precision (yellow) and recall (green) over all participants is depicted for the best model SVM-SS using a) asymmetry features and b) all features. Each three task and their average is shown.

the mean classification accuracy of 78% which coincides with the findings from the personalized model. Additionally, the classifiers outperforms when all the feature set is used with the mean accuracy of 88%.

Table 4: Mean of the accuracy (acc), f1_score, precision and recall of the generalized model using asymmetry features and all the features.

features	acc	f1_score	precision	recall
asy	0.78	0.81	0.79	0.84
all	0.88	0.90	0.86	0.94

3.4 Self-Reported Labels

The third experimental evaluation was performed by labelling the data as *high* and *low* cognitive load by applying a threshold over the mean of self-reported Nasa-TLX score from table 1 for each participant. We developed both personalized model and generalized model as mentioned in section 3.2 and 3.3, respectively. As illustrated in table 5, the SVM-SS showed the best accuracy across all the features sets for both

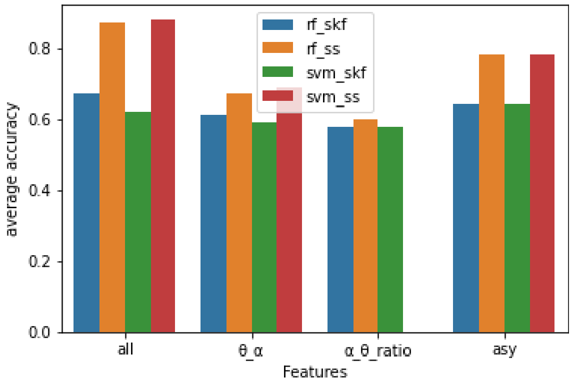
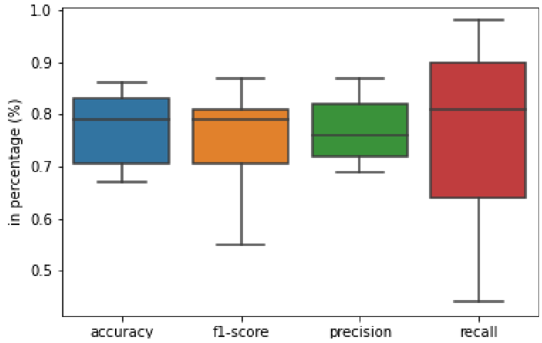


Figure 7: The features (x-axis) and the corresponding mean classification accuracy over all the tasks (y-axis) is plotted for all the four classifier.

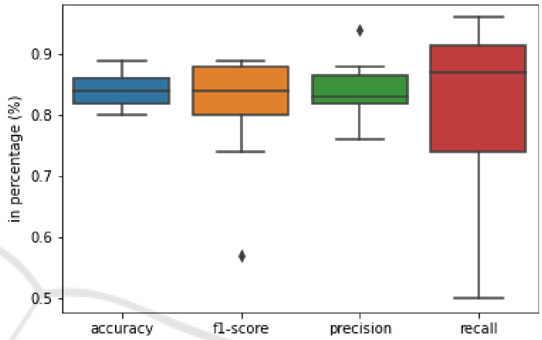
models. For the personalized model θ_α and asymmetry features provides similar performance of the model evaluation whereas the model using all the features performed better. Furthermore, for the generalized model the accuracy barely reached chance level while using θ_α and the θ_α_ratio features but reached to 73% using asymmetry features which further increased by 10% while using all the features. The distribution of the personalized classification accuracy and the f1_score, precision and recall over all the participants is provided in the figure 8.

Table 5: Classification results for personalized and generalized model using self-reported labels for the three cognitive load tasks for SVM and RF classifiers with both the SKF and SS cross-validation using four feature sets.

Features	**Classifier -CV**	**Per.**	**Gen.**
all	rf-skf	0.77	0.53
	rf-ss	0.83	0.81
	svm-skf	0.78	0.52
	svm-ss	**0.84**	**0.83**
θ_α	rf-skf	0.67	0.47
	rf-ss	0.69	0.54
	svm-skf	0.68	0.48
	svm-ss	**0.7**	**0.57**
θ_α_ratio	rf-skf	0.66	0.51
	rf-ss	0.66	0.52
	svm-skf	0.67	0.52
	svm-ss	**0.69**	**0.56**
asy	rf-skf	0.77	0.51
	rf-ss	0.78	0.73
	svm-skf	0.74	0.73
	svm-ss	**0.77**	**0.73**



(a) asymmetry features



(b) all features

Figure 8: The distribution of test accuracy, f1_score, precision, and recall over all participants are depicted for the best model SVM-SS using a) asymmetry features and b) all features.

4 DISCUSSION

This paper evaluates cognitive load classifiers by acquiring data using wearable EEG devices containing only four dry electrodes. Within the experimental protocol, the brain activity data and the self-reported questionnaires (e.g., Nasa-TLX) from eleven participants were recorded while watching a relaxation video and performing three cognitive load tasks: Reading Span, Stroop, and N-back. After pre-processing the raw EEG data using outlier rejection based on a movement filter, spectral filtering, common average referencing, and normalization, frequency-domain features were extracted from 30-second windows. The features were grouped into four different sets to perform the binary classification. The θ_α feature contains mean θ and mean α band powers across all four channels. According to the literature, the α band power decreases with increasing cognitive load, and the θ band power behaves oppositely (Antonenko et al., 2010). Since lately the ratio of these two frequency bands was also studied, we included the ratio in the θ_α_ratio feature set (Raufi and

Longo, 2022). Additionally, according to the physiological assumptions, the right alpha power is reduced than the left alpha power under the load condition. Therefore, we extracted the asymmetry features from all five frequency bands and the frontal asymmetry of the α frequency band.

To begin with the evaluation, we performed feature exploration that the θ power increases and α power decreases in a personalized manner for most tasks. These individual feature characteristics are aligned with the literature. Moreover, the mean asymmetry score across all tasks and participants was higher for relaxation sessions than cognitive load sessions. Though the difference in the asymmetry score is statistically insignificant, internal testing shows that for some of the sessions, the score is significantly higher in the relaxation session.

After feature exploration, we evaluated personalized and generalized models utilizing the four feature sets for binary classification using SVM and RF classifier with both SKF cross-validation with 8-folds and SS cross-validation with 9-splits and test size of 0.25, respectively. The SVM-SS classifier performed best for the personalized model for all the feature sets and for most feature sets of the generalized model. Therefore, for a fair comparison we considered explaining the results from SVM-SS classifier. Further results show that the asymmetry feature set outperforms the θ_α and the $\theta_\alpha_$ratio feature sets with a mean classification accuracy of 81.7% for the personalized model and 78% for the generalized model. Moreover, the authors report 77.9% of accuracy while using only EEG asymmetry features (Ahn et al., 2019). Another group of authors reported higher classification accuracy using the asymmetry features, but they fell short of reporting other evaluation matrices, and the work also needs to be validated for a larger cohort (Arpaia et al., 2020). However, while using all the features, the mean classification accuracy was 90.3% for the personalized models and 88% for the generalized model. The performance of the personalized model is significantly better, considering the fact that the authors used 24-channel EEG data and achieved 75.9% accuracy (Pang et al., 2021). While considering the generalized model, the authors achieved only 3% higher accuracy than the reported results in this paper while using a clinical-grade EEG device (Jiménez-Guarneros and Gómez-Gil, 2017).

It is concluded that a combination of physiological and subjective measures is most effective in detecting changes in intrinsic cognitive load. Furthermore, to evaluate the correlation between self-report and physiological data, we evaluated personalized and generalized models based on self-reported labels. The binary classification accuracy of the three tasks for the personalized and generalized models was 84% and 83%, respectively. The results objectify the findings of the literature of including both physiological and subjective methods to measure cognitive load (Ayres et al., 2021). These findings will support the daily life use cases where we will not have an explicit cognitive load sessions other than self-report.

As a future work, different window lengths can be analysed for classification since the literature show the best performance on a 120-second window using the same device as in this paper (Bashivan et al., 2016). The fixed threshold movement filter used in the pre-processing step can be replaced by more advanced filtering techniques, such as adaptive filtering, in the future. Moreover, the findings on the asymmetry features lead to work more on extracting high-level features (e.g., mean, median, kurtosis) from the asymmetry features to outperform the classification accuracy using all features. Additionally, the findings on the feature exploration and classification on the personalized models will be considered to provide a solution to develop a pre-trained generalized model to update the individual data received. The results could also be evaluated on the individual demographics(i.e., age, gender) of the participants. Moreover, the randomization of the tasks in the future experimental protocol can reduce the bias of cumulative load and may pave the way to improve the self-report label for classification. The experimental paradigm will be made more robust by utilizing the coder view of Psychopy and be publicly available in the future. Eventually, the usage of commercial-grade EEG sensors only with fewer electrodes will provide a way for the extensive use of the EEG devices in daily life.

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