

INTRODUCTION

For a brain-computer interface (BCI) to be operational, a calibration phase is necessary because of the intra- and inter-subject variability of electroencephalographic (EEG) signals. This reduces the limited available time to use the BCI, and induces fatigue in the subject. **Goal: find a classification method that requires minimal training trials while maintaining high classification accuracy.**

In this study, the classification task is between a motor imagery (MI) of an upper limb and a resting period. We compare classification methods with a feature extraction step that rely on latent spaces: **EEGNet** [1], Common Spatial Pattern (**CSP**) followed by Linear Discriminant Analysis (**LDA**) and a Self-Supervised Learning (SSL) approach called **SSL-RP** (Relative Positioning pretext task) [2].

SSL generates a large amount of self-labeled data, using a minimal training set, to learn features for the MI detection task. They are the result of a projection on a latent space, which strongly impact the classifier's performance.

Uniform Manifold Approximation and Projection (**UMAP**) [3] is a dimensionality reduction method that tries to reproduce the topology of a high-dimensional space in a lower-dimensional space. It preserves the global structure of the data and is faster than other approaches, such as t-SNE [4].

Hypothesis: by adding a UMAP projection to the SSL-RP method, the MI and resting periods will be more easily distinguishable by the classifier.

MATERIAL & METHOD

Material:

The dataset 2a of the BCI competition IV contains recordings of 9 subjects performing 4 MI tasks, of which only right and left hand MI were used for this study. EEG signals were recorded with 22 electrodes at a sampling rate of 250 Hz. Training (session 1) and test (session 2) sets are composed of 6 runs, each of 12 trials per MI task. From 8 to 72 trials were used to learn the model.

Method:

- **SSL-RP** builds a latent space according to EEG segments' distance in time.
- **EEGNet** has $C=22$ channels, $T=512$ Hz, $F_1=8$ temporal filters of size $K_1=(1, 32)$, $D=4$ spatial filters of size $K_2=(22, 1)$, a depthwise convolution filter of size $K_3=(1, 4)$ and $F_2=16$ pointwise convolution filters.
- **UMAP** takes into account the number of neighbors $n=2$ (local scale at which the manifold is approximated) and the minimal distance $m=0.1$ (how tightly packed are points in the low dimensional space).

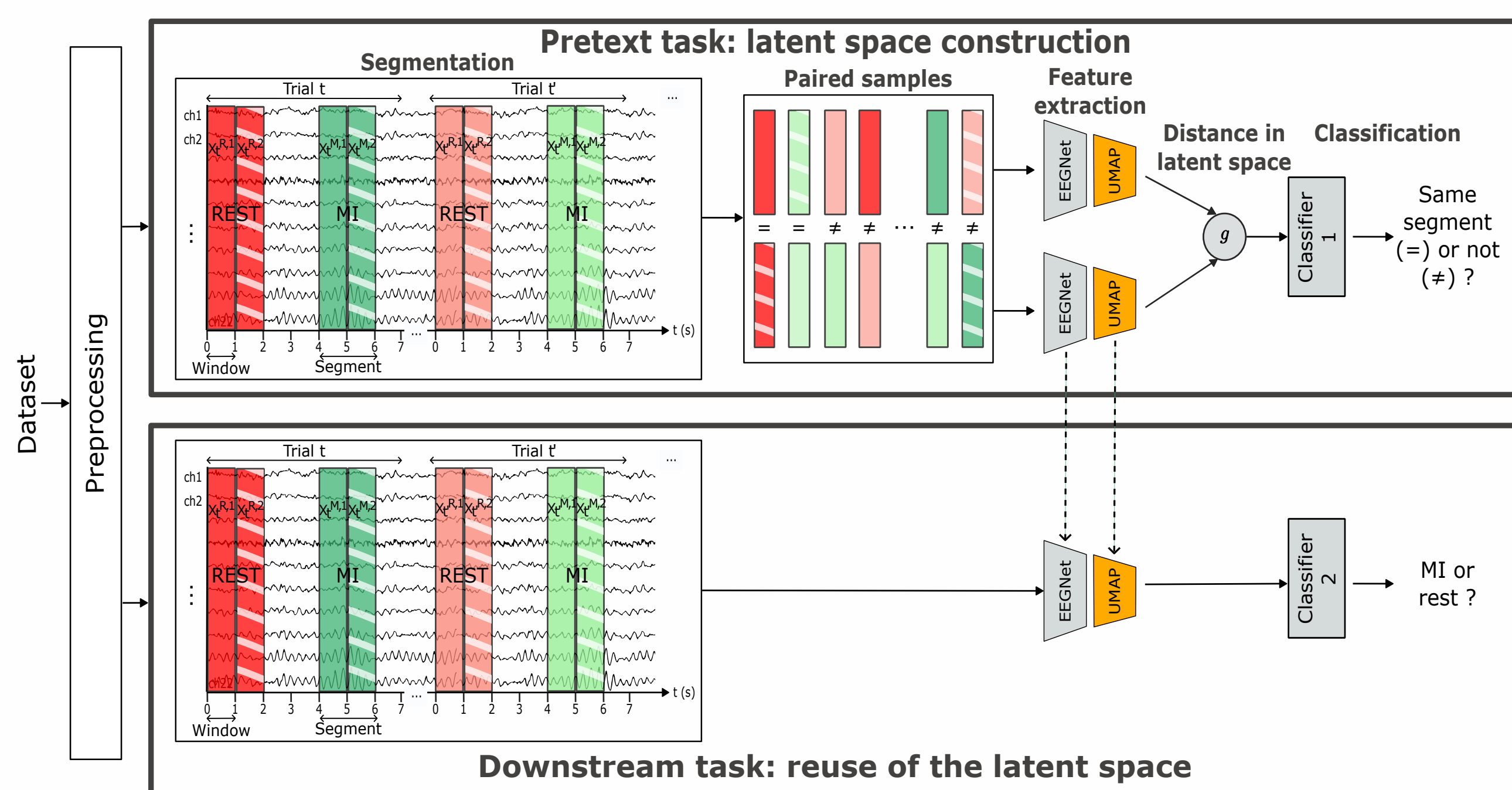


Fig. 1: Structure of the SSL-RP-UMAP model (figure inspired by [5]). MI and rest segments are selected from each trial and divided into windows. Positive and negative pairs of windows are used for the pretext task, to train the features' extractor. During the downstream task, EEGNet and UMAP are reused to project the data, where the second classifier will determine if the window corresponds to MI or rest class.

RESULTS

At first, UMAP was used to visualize the training data features vectors obtained by EEGNet, where a 2D-space seems to be enough for the two classes to be well separated. However, the testing set is still tangled.

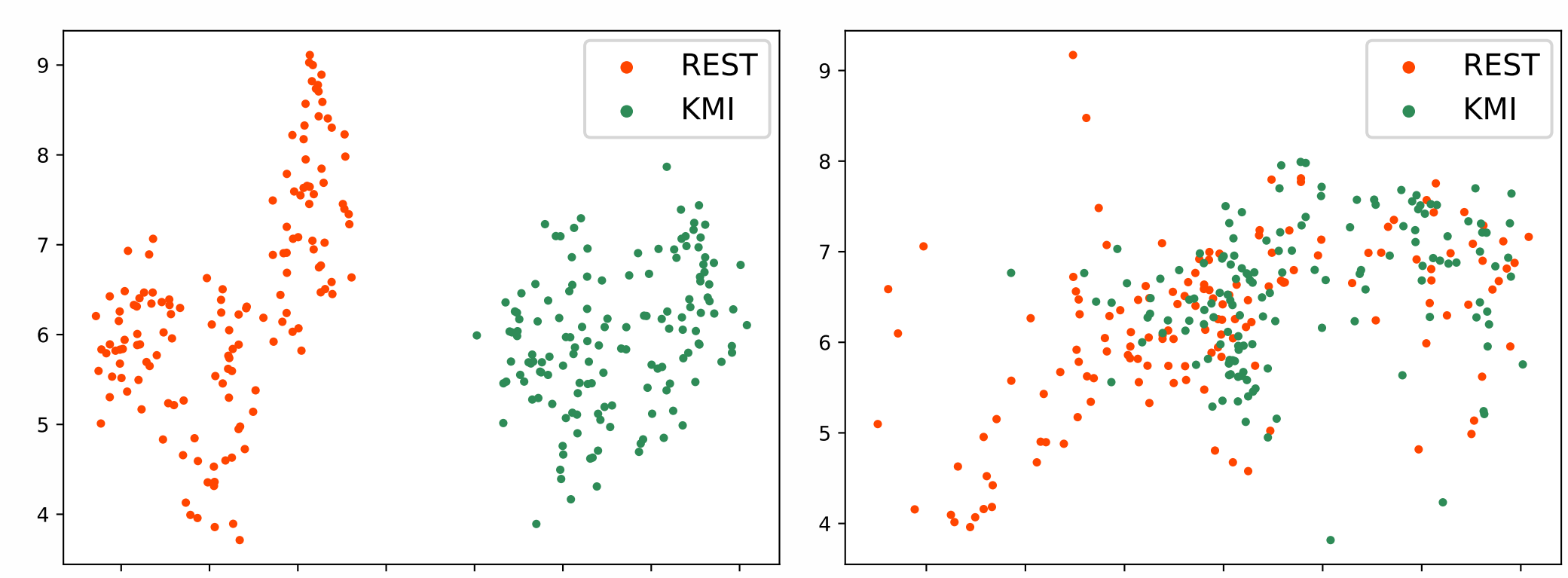


Fig. 2: Projections in a 2D-space of the MI and rest train (left) and test (right) features of subject n°3, obtained by the UMAP algorithm during the downstream processing chain. All 72 trials were used.

Several models were tested on the MI vs rest classification:

- The SSL-RP method performs better when only EEGNet features are extracted. The UMAP projection seems to alter the shape of the latent space in a way that impairs classification.
- CSP+LDA and EEGNet have better performances than both self-supervised models, SSL-RP and SSL-RP-UMAP.

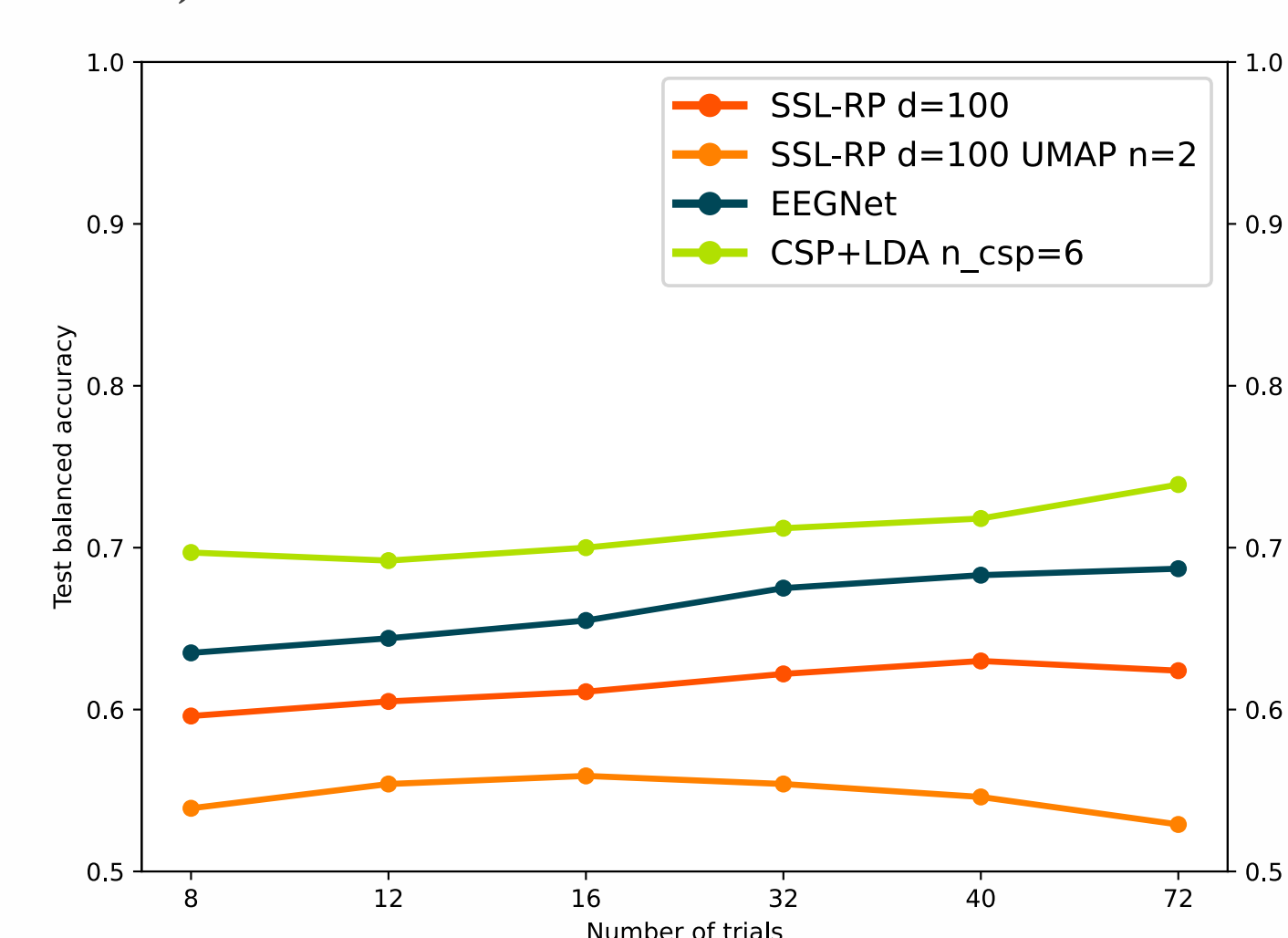


Fig. 3: Test accuracy averaged across all 9 subjects, for the detections of right or left hand MI vs rest, obtained by the three models, according to the number of training trials. These sequential trials were randomly selected and the process was averaged for 10 repetitions.

CONCLUSION

Discussion:

- The addition of a **UMAP projection does not facilitate the recognition of MI periods**, as compared to when only EEGNet is the feature extractor.
- The negative (far) pairs of EEG windows may be from the same class. UMAP will keep the positive pairs together and negatives apart, emphasizing the distance between pairs of the same class. Thus, it is difficult for a simple logistic regressor to distinguish these classes.

Interesting leads:

- Because of the pretext task sampling method, a k-means approach might be more appropriated than a logistic regression.
- Using UMAP as unique feature extractor for the SSL-RP method.
- Using a larger database, like Cho2017 [6], with 52 subjects.

References:

- [1] V. J. Lawhern et al. *EEGNet: a compact convolutional neural network for EEG-based brain-computer interfaces*. Journal of Neural Engineering, 2018.
- [2] H. Banville et al. *Uncovering the structure of clinical EEG signals with self-supervised learning*. J. Neural Eng, 2020.
- [3] L. McInnes et al. *UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction*, 2018.
- [4] L. van der Maaten and G. Hinton. *Visualizing data using t-SNE*. J. Mach. Learn. Res, 2008.
- [5] Y. Ou et al. *An improved self-supervised learning for EEG classification*. Mathematical Biosciences and Engineering, 2022.
- [6] H. Cho, M. Ahn, S. Ahn et al. *EEG datasets for motor imagery brain computer interface*. GigaScience Database, 2017.

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