Supplementary Materials

A. Datasets and EEG Pre-process

A semi-simulated EEG dataset, an EEG dataset of Autism Spectrum Disorders children, and a resting-state EEG dataset of normal adults are constructed to evaluate the performance of these bad EEG epoch rejection methods.

1) Semi-simulated EEG Dataset: Semi-simulated EEG Dataset[1] is constructed by synthesizing pure EEG with dedicated artifacts or noise signals. The overview of construction is shown in Fig. 1. Pure EEG are obtained from public dataset [1] which provides the EEG recordings from 36 subjects on mental arithmetic task (MAT). The recordings of the background EEG of all subjects (before MAT) are selected as the source of pure EEG for less potential interference. All recordings used are artifact-free EEG epochs of 60 seconds duration with 19-channel electrodes[2]. Non-overlapping sliding windows with a length of 10 seconds (2560 data samples) are applied to segment each channel EEG recordings and a total of 4104 one-dimensional pure EEG epochs are obtained. Artifacts and noise sources include five typical artifacts (EMG, EOG, ECG, EM, and BW) and specific noise signals (Gaussian white noise, Square wave, and sawtooth wave), where the artifacts are derived from multiple real datasets [1]–[6] and the latter is simulated via the program. The operations described in reference [7] are used to pre-process the artifact data for obtaining pure data, which mainly includes filtering and segmentation.

Semi-simulated raw EEG are simulated by contaminating pure EEG with mixing additional artifacts or noise signals, according to Eq.(1).

$$EEG_R \ or \ EEG_B = EEG_P + \lambda \cdot N, \quad (1)$$

where EEG_R, EEG_B,EEG_P, and N denote the raw EEG, bad EEG, pure EEG, and noise signals (includes artifacts), respectively, and λ denotes a hyperparameter that controls the SNR of EEG_R. The desired SNR of EEG_R is obtained by changing λ according to Eq.(2).

$$SNR = 10log\frac{RMS(EEG_P)}{RMS(EEG_R \ or \ EEG_B)}, \quad (2)$$

where RMS is the root-mean-square energy of the signal.

The synthesis process consists of two stages: **Normal** raw EEG acquisition and **Bad** raw EEG acquisition. In this study, the assumption is made that the entire normal EEG epoch is subject to slight influences from artifacts. Therefore, in the first stage, each pure EEG epoch undergoes complete contamination with artifacts. One artifact type (including five artifacts and their hybrid artifacts after combining them with each other) is first randomly selected for each EEG epoch, then one corresponding type artifact epoch is randomly selected, and finally, a value of SNR level is randomly determined within the range of [-5, 2] dB for pairwise synthesis, which completes the synthesis of the normal EEG. The contamination of the bad epoch is not performed in the whole epoch. The starting and ending points of the bad epoch are first randomly determined separately, and then the corresponding raw EEG epoch is intercepted for the next synthesis step. The synthesis of the bad EEG epoch is similar to the former, again in a randomized manner to determine artifact type and SNR level values. The difference is the addition of three contaminant types, Gaussian white noise, square wave, and sawtooth wave as well as a change in the range of SNR level values to [-15, -5] dB. Note that an additional data manipulation of amplitude reduction (scaling coefficient is [0, 0.33]) is added to simulate the phenomenon of electrode detachment leading to a flat line signal.

2) ASD EEG Dataset: ASD EEG Dataset is constructed based on the Autism Spectrum Disorder (ASD) EEG recordings obtained from the State Key Laboratory of Cognitive Neuroscience and Learning at Beijing Normal University. The EEG dataset records resting-state EEG signals from 66 autistic children and 18 healthy children aged 3-6 years old in total with a sampling rate of 1000 Hz and eight electrodes[3], following the guidelines of the international 10–20 system. The longest recording duration for a single subject in the dataset was 11 minutes and 20 seconds, the shortest was 2 minutes, and the average recording duration was approximately 8 minutes and 20 seconds. More details about this dataset could be available in study [8]. Non-overlapping sliding windows of 10 seconds duration are used to intercept the data of each channel.

3) rs-EEG Dataset: rs-EEG Dataset includes the resting-state EEG from three normal adult males (ages 25, 28, and 29 years). The acquisition equipment is the same as in ASD EEG Dataset, so the electrode arrangement and sampling rate are also the same. Relatively speaking, the probability of occurrence of bad epoch events in raw EEG has a large difference from that of normal epoch. As a result, the recorded performs various irregular collection behaviors to obtain more samples of bad epochs during the recording of this dataset. Similarly, non-overlapping sliding windows of 10 seconds duration are used to intercept the data of each channel.

4) Data Pre-processing and Annotation: After the construction of datasets, the EEG data have been resampled to 256 Hz and segmented into sequences of 5 consecutive

[1]Authorized for open access at the website: https://github.com/GTFOMG/EEGEpochNet-project.

[2]Fp1, Fp2, F3, F4, F7, F8, T3, T4, C3, C4, T5, T6, P3, P4, O1, O2, Fz, Cz, Pz

[3]Fp1, Fp2, C3, C4, T3, T4, O1, O2

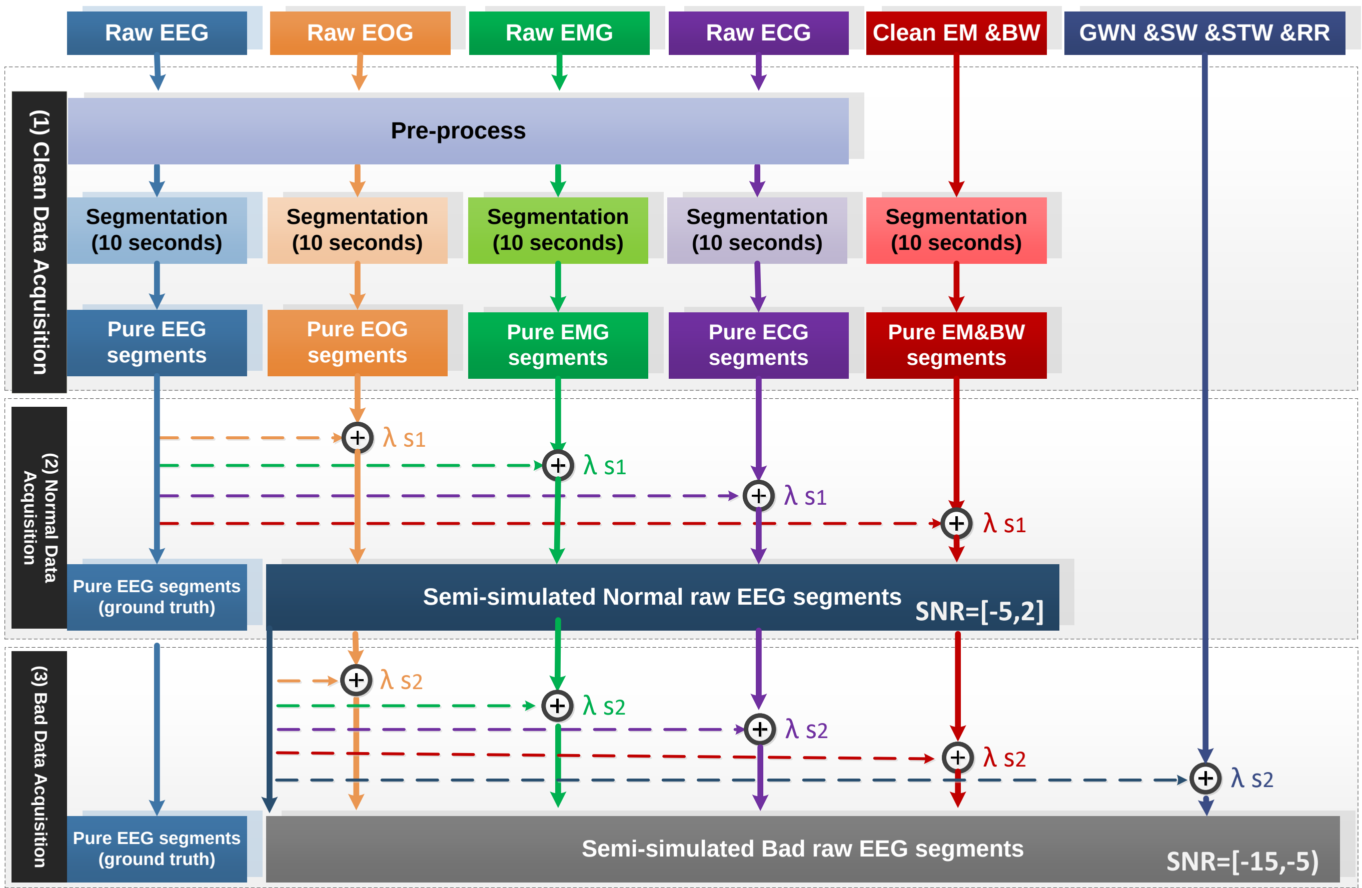


Fig. 1: Pipeline of Constructing the Semi-simulated Raw EEG Dataset. λ_{s1} and λ_{s2} correspond to the control hyperparameters for the different phases, respectively.

TABLE I: Detailed Statistics of the Datasets

	Number of 10s Sequence	Number of Normal Epoch(%)	Number of Bad Epoch(%)
Semi-simulated EEG Dataset	4,104	11,773 (57.37%)	8,747 (42.63%)
ASD EEG Dataset	7,500	22,604 (60.28%)	14,896 (39.72%)
rs-EEG Dataset	976	3,411 (69.89%)	1,469 (30.10%)

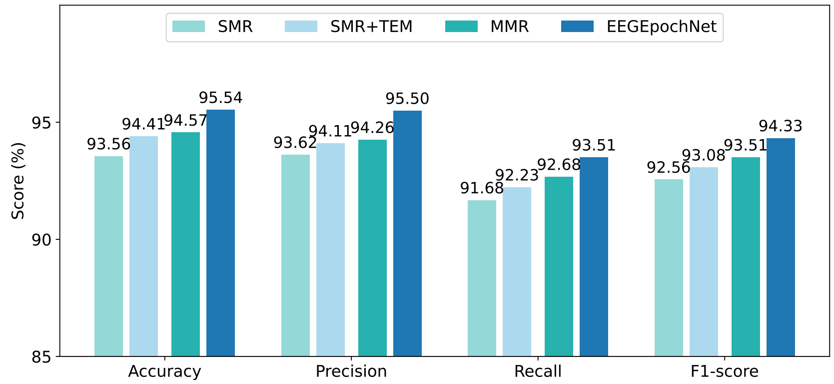
epochs (format: N, 5, 512). The subsequent pre-processing steps are mainly filtering and normalization. The EEG data are filtered with a 0.5-80 Hz second-order Butterworth band-pass filter and a 50 Hz notch filter. Subsequently, the EEG data are normalized by subtracting the mean and dividing by the standard deviation of the input signals in the training set. *EEGEpochNet* is designed for a single-channel EEG epoch rejection task with channel insensitivity. Considering the specificity of EEG at multiple levels (channel, individual or group, etc.), the computation of normalization parameters oriented to different task goals should be different. As the single-channel models, the normalization parameters consist of one channel-independent mean and standard deviation computed after pooling all channels. More different manners of calculating the normalization parameters will be described in detail when covered in subsequent analyses.

In this study, a 2-second duration epoch is regarded as a bad epoch rejection unit, and the **Normal** and **Bad** annotations are used to provide a label for each epoch. A length of 2 seconds is chosen since this is considered a decent resolution to capture typical characteristics for EEG analysis. Two EEG experts review and annotate every epoch. For each epoch, if more than 50% (i.e. 1 s) is annotated as **Normal** or **Bad**, it is labeled as such. Additionally, epochs that contained short (<1 s) bad epochs that started and ended within that same epoch are also labeled as **Bad**. For epochs that are inconsistently labeled by experts, they are labeled more than 2 more times. Sequences with epochs that do not have a consensus label after three times of annotations will be removed from the corresponding dataset. Given the imbalance in the prevalence of these two events, several **Normal** EEG epochs are randomly deleted for balance. The table I provides statistical information on the two types of epochs for each dataset.

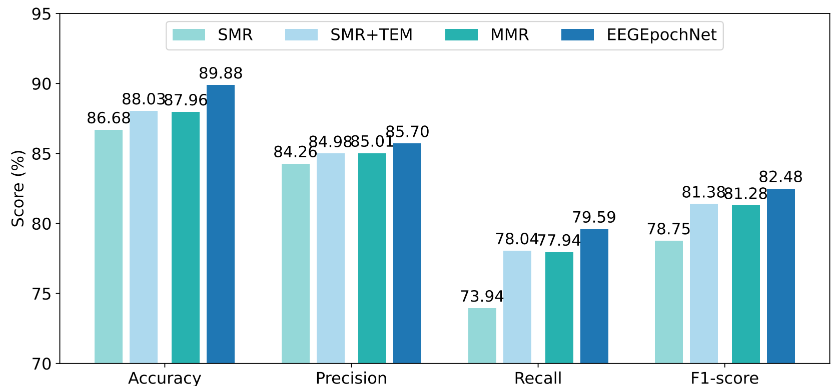
B. More results of the Performance Evaluation

References

[1] I. Zyma, S. Tukaev, I. Seleznov, K. Kiyono, A. Popov, M. Chernykh, and O. Shpenkov, “Electroencephalograms during mental arithmetic task performance,” *Data*, vol. 4, no. 1, 2019.



(a) ASD EEG Dataset



(b) rs-EEG Dataset

Fig. 2: Validation of the Design Effectiveness of EEGEpochNet Modules.

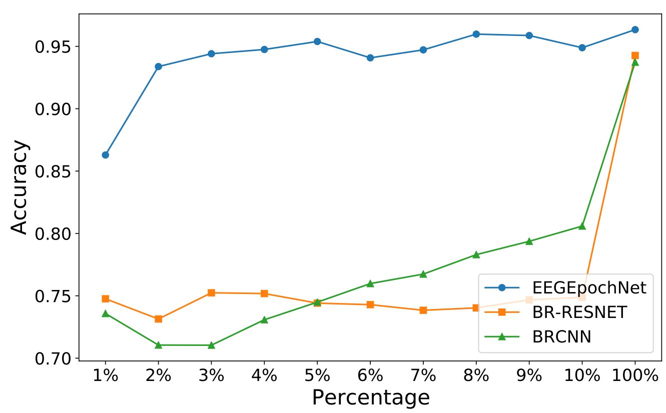


Fig. 3: Model Performance Using Different Amount of Labeled Data (ASD EEG Dataset).

[2] A. Schlögl, C. Keinrath, D. Zimmermann, R. Scherer, R. Leeb, and G. Pfurtscheller, “A fully automated correction method of EOG artifacts in EEG recordings,” *Clinical Neurophysiology*, vol. 118, no. 1, pp. 98–104, 2007.

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[5] G. Moody and R. Mark, “The impact of the mit-bih arrhythmia database,” *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001.

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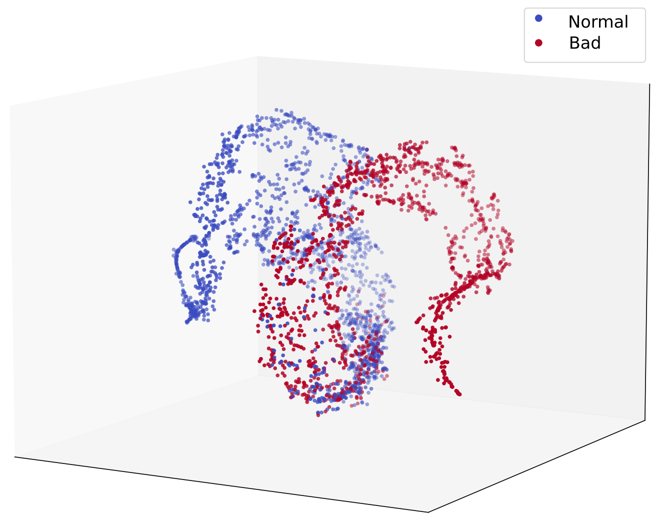
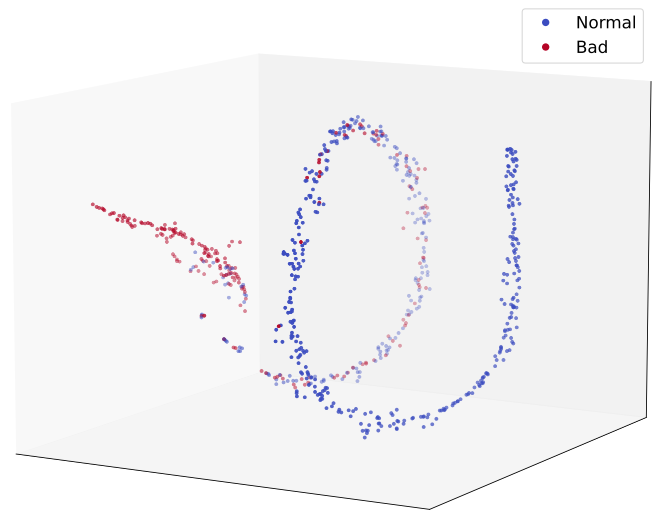
[7] T. Gao, D. Chen, Y. Tang, Z. Ming, and X. Li, “EEG reconstruction with a dual-scale cnn-lstm model for deep artifact removal,” *IEEE Journal of Biomedical and Health Informatics*, vol. 27, no. 3, pp. 1283–1294, 2023.

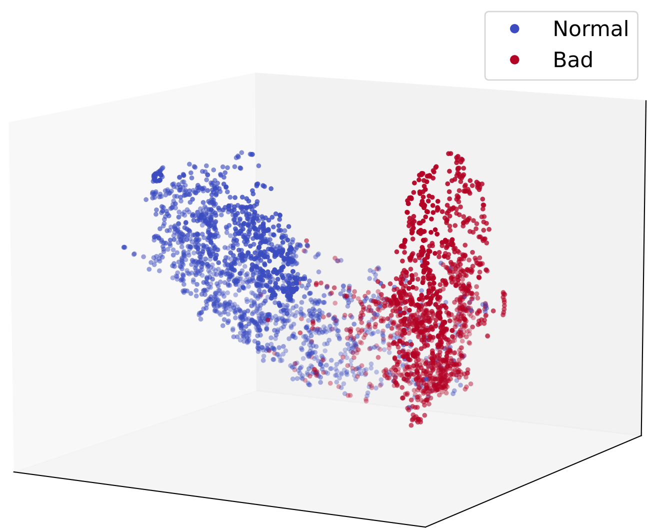
[8] H. Dong, D. Chen, L. Zhang, H. Ke, and X. Li, “Subject sensitive EEG discrimination with fast reconstructable CNN driven by reinforcement learning: A case study of asd evaluation,” *Neurocomputing*, vol. 449, pp. 136–145, 2021.



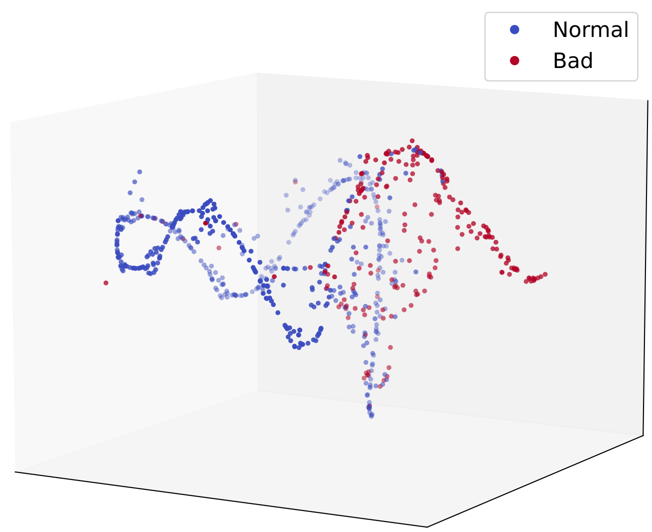
(a) Visualization of features before fine-tuning (Semi-simulated EEG Dataset)



(b) Visualization of features before fine-tuning (rs-EEG Dataset)



(c) Visualization of features after fine-tuning (Semi-simulated EEG Dataset)



(d) Visualization of features after fine-tuning (rs-EEG Dataset)

Fig. 4: EEGEpochNet Feature Representation Before and After Fine-tuning t-SNE Visualization.