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BRAIN COMPUTER INTERFACE

Deep learning techniques for denoising EEG data

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1 Introduction

EEG data is often contaminated by noise, which is any unwanted signal that interferes with the true brain signal. Noise reduces the quality and reliability of EEG data. It is for this reason that denoising of EEG data is an important task in the process of EEG signal analysis.

Two common types of noise that affect EEG data are EOG (electrooculography) and EMG (electromyography). EOG is the noise caused by the eye movements and blinks. EMG is the noise caused by the muscle contractions, such as facial expressions, chewing, or head movements.

The aim of this paper is to explore the possibilities of using deep learning techniques to automate and facilitate EEG signal denoising.

2 Dataset

During the creation of this paper, multiple datasets were expolred. The original objective was to use a dataset of continuous recordings from widely available EEG headsets. All channels should have been used. However, several issues with these datasets were encountered, including missing key information like information about reference and exact preprocessing steps. The most common problem being the misalignment of raw and clean data, which made it impossible to use such datasets for training.

2.1 Naturalistic Music EEG Dataset—Hindi (NMED-H) 2.0

[3] The raw data in this dataset does not match the clean data. The clean data is aggregated by stimulus in contrast to raw data being provided as single recordings.

2.2 A Large EEG Dataset for Studying Cross-Session Variability in Motor Imagery Brain-Computer Interface

[4] The dataset is completely missing raw data. Both `.mat` and `.edf` contain the same data, which is already preprocessed.

2.3 A Dataset of Scalp EEG Recordings of Alzheimer's Disease, Frontotemporal Dementia, and Healthy Subjects from Routine EEG

[1] The raw and clean data use a different reference. Data from reference nodes A1 and A2 are not included in the raw data. This makes it impossible for the model to learn anything meaningful.

2.4 SRM Resting-state EEG

[2] This dataset from Oslo university looked as an ideal candidate, but during preprocessing some epochs in the clean data were deleted. That leads to a mismatch in length between raw and clean data.

2.5 EEGdenoiseNet: a benchmark dataset for deep learning solutions of EEG denoising

[5] The dataset was created as a benchmark of deep learning models for denoising. The authors aimed to address the lack of well-structured and standardized datasets. It consists of clean EEG, EOG only and EMG only segments. The paper contains information on how to create semi-synthetic data with artifacts using the formula:

$$y = x + \lambda \times n \tag{1}$$

The SNR of the epoch can be adjusted by:

$$SNR = 10 \log \frac{RMS(x)}{RMS(\lambda \times n)} \tag{2}$$

that allows the model to learn different levels of noise.
For the reasons stated above, this dataset was chosen as the best fit for the purposes of this paper.

3 Models and Results

Several models have been explored and tested. As the task is simple in terms of deep learning, the models used are mainly the basic ML models. Using complex models like VGG, Resnet, GANs would lead to significant overfitting. Each model was tested in different vatiations with different parameters.

3.1 FCNN

FCNN 1 is fully connected neural network model with 5 layers, 512-1024 neurons per layer and leaky relu activation function. FCNN has the same structure but adds a dropout to each inner layer to prevent overfitting.

3.2 LSTM

LSTM is a long short term memory neural network with 1 LSTM layer of dimensions 256. The input and output is scale with linear layers.

3.3 CNN

CNN 1 is a convolutional neural network with 5 convolutional layers for downscaling and 5 for upscaling. The kernel size is 2. The activation function used is leaky relu. CNN 2 is a smaller network with only 3+3 convolutional layers but greater amount of convolutional filters. CNN 1 was the only model to not overfit, but the overall performance was not excellent. CNN 3 reduces the number of convolutional layers to 2+2 but adds batch normalization and dropout to each layer. The final layer is fully connected.

3.4 Metrics

	R2	MAE	MSE	RMSE
FCNN 1	0.44	0.59	0.56	0.75
FCNN 2	0.36	0.63	0.64	0.80
LSTM	0.47	0.57	0.53	0.72
CNN 1	0.53	0.52	0.47	0.66
CNN 2	0.55	0.51	0.45	0.64
CNN 3	0.62	0.48	0.38	0.61

It can be clearly seen that CNNs outperform FCNN and LSTM networks, which both are prone to overfitting.

4 Experiments

Experiments were conducted on both EOG and EMG artifacts. The models were trained on both artifacts at the same time. The best performing model (CNN 3) was then trained independently on each of the artifacts, this led to slightly better results for the trained artifact, but also a significantly worse for the other. The trade-off will not be worth in most of the cases.

4.1 EOG Artifacts

The results of the denoising of EOG artifacts will be shown on the example in figure 1.

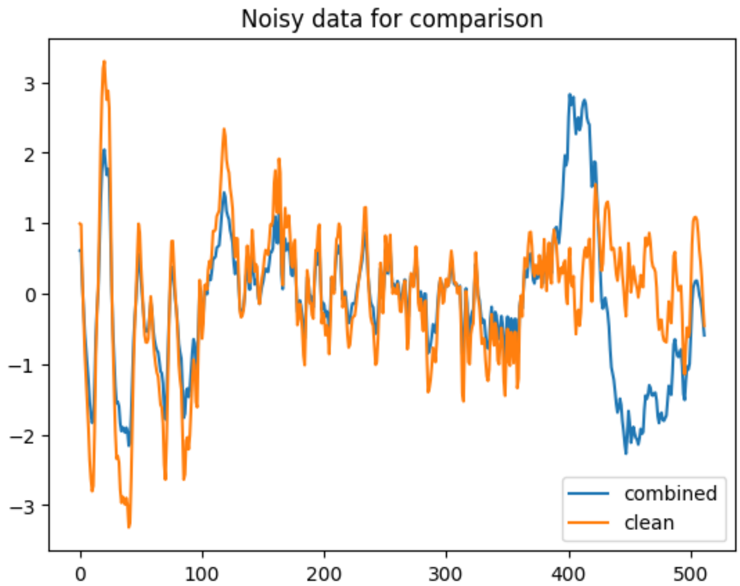

Figure 1: Tested EOG artifact

4.1.1 FCNN

The added dropout layers in FCNN 2 caused a *smoothing* of the resulting signal which led to a decrease of overall performance.

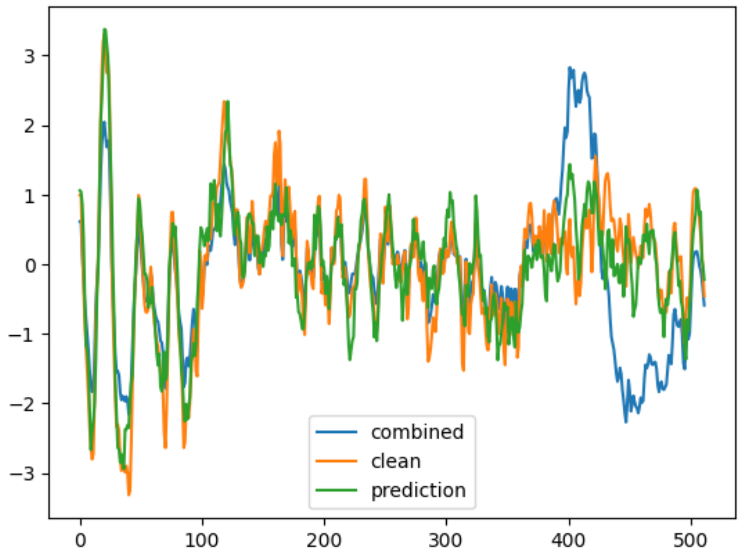

Figure 2: FCNN 1 EOG

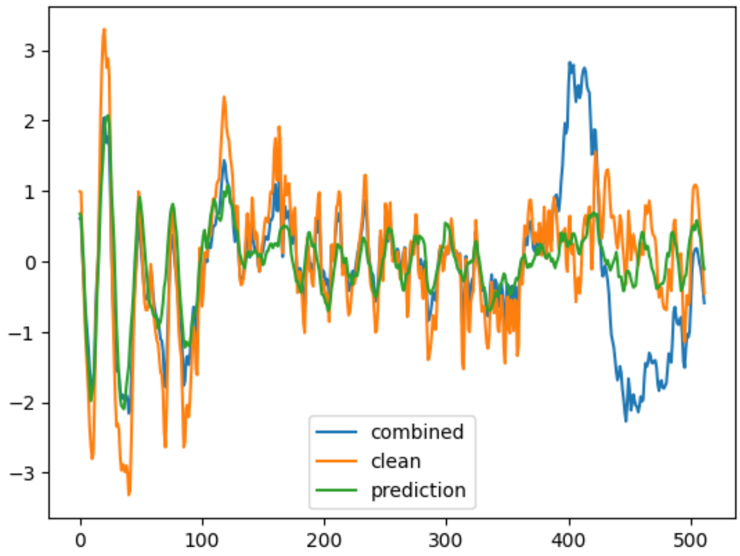

Figure 3: FCNN 2 EOG

4.1.2 LSTM

The LSTM model also adds a *smoothing* of the resulting signal.

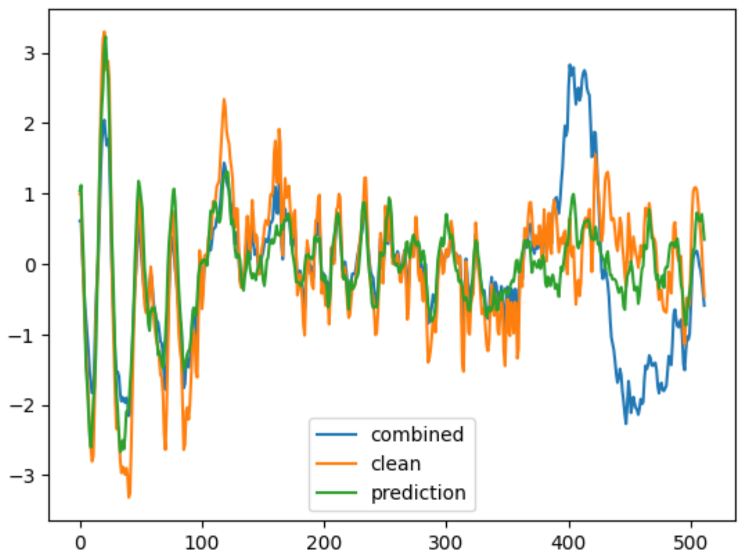

Figure 4: LSTM EOG

4.2 CNN

The CNN 3 model is best at predicting the clean signal.

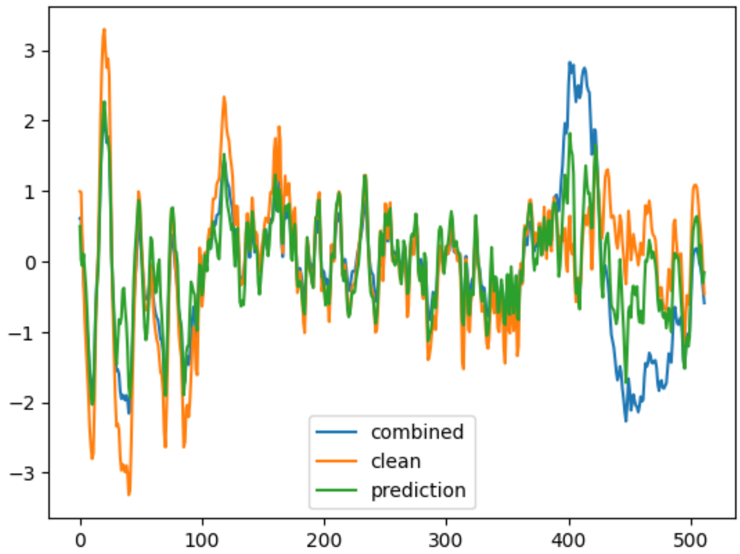

Figure 5: CNN 1 EOG

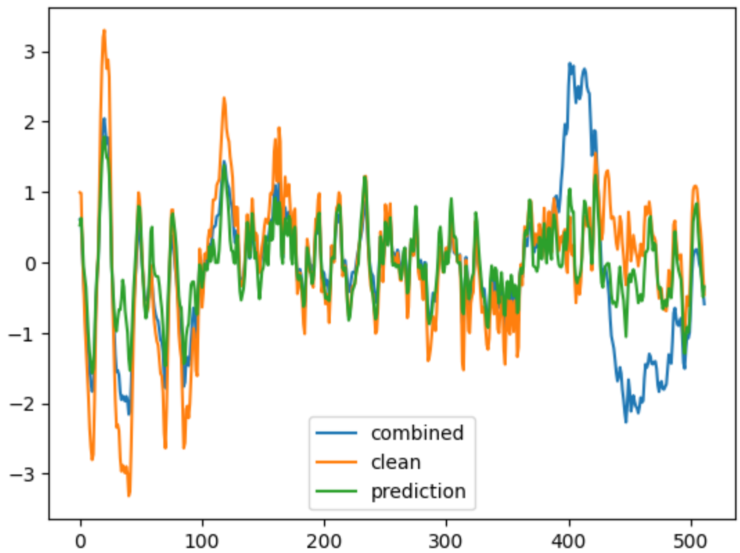

Figure 6: CNN 2 EOG

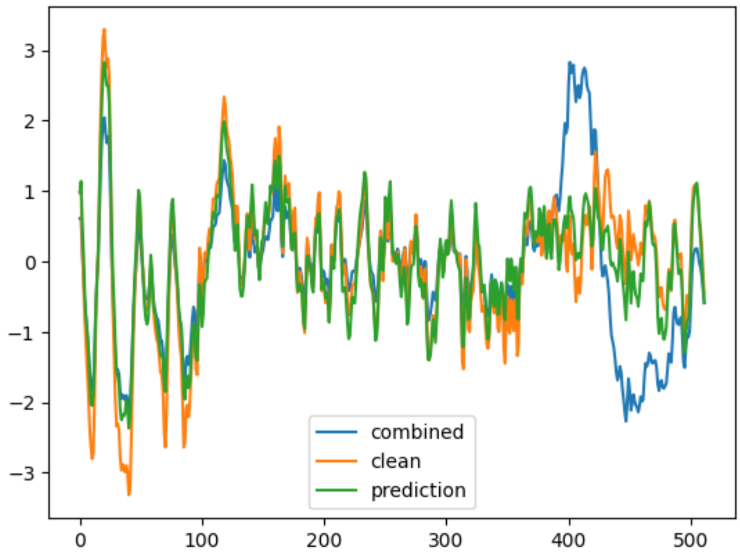

Figure 7: CNN 3 EOG

4.3 EMG Artifacts

The results of the denoising of EMG artifacts will be shown on the example in figure 8. The results are similar to the results of EOG artifacts.

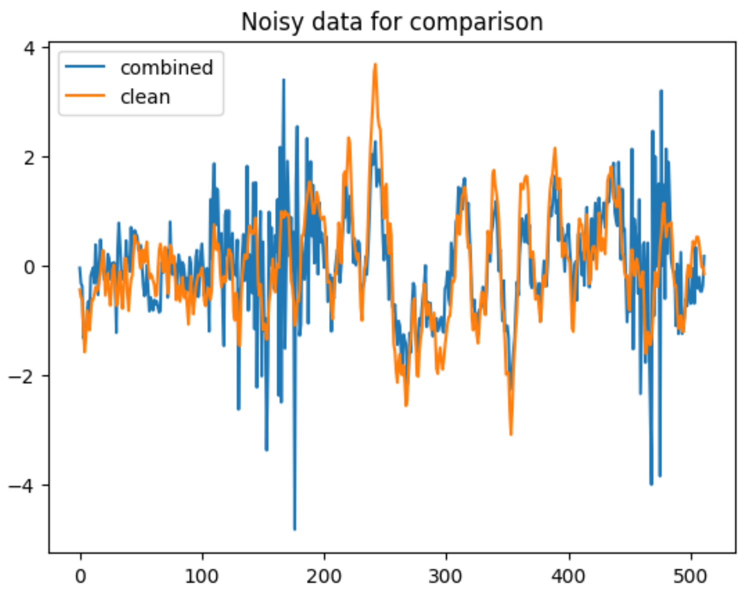

Figure 8: Tested EMG artifact

4.3.1 FCNN

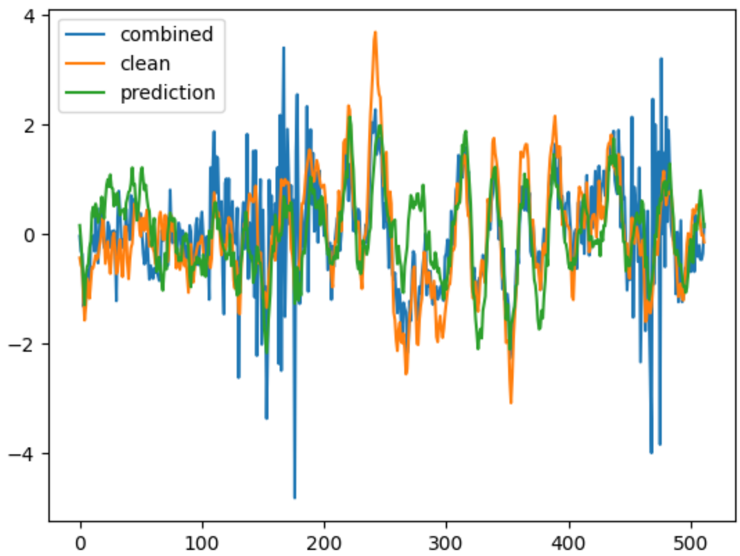

Figure 9: FCNN 1 EMG

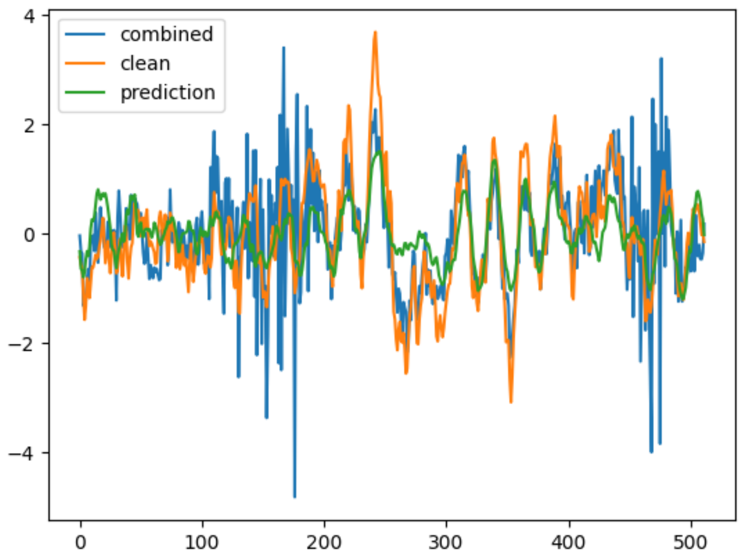

Figure 10: FCNN 2 EMG

4.3.2 LSTM

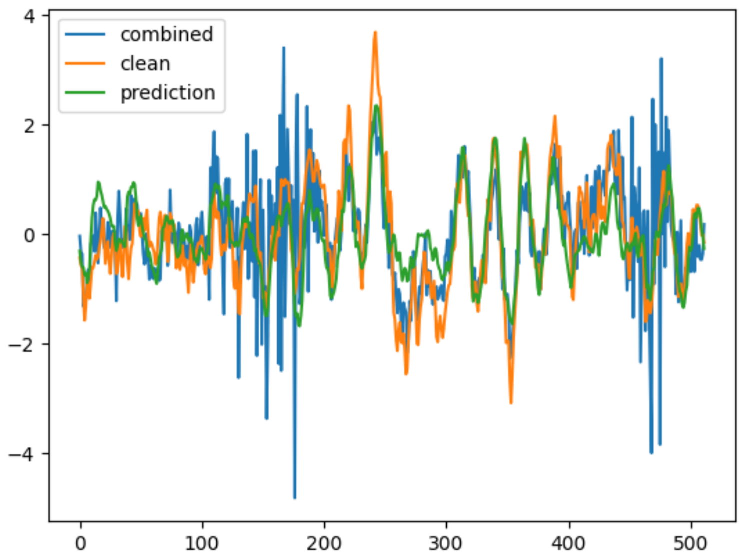

Figure 11: LSTM EMG

4.4 CNN

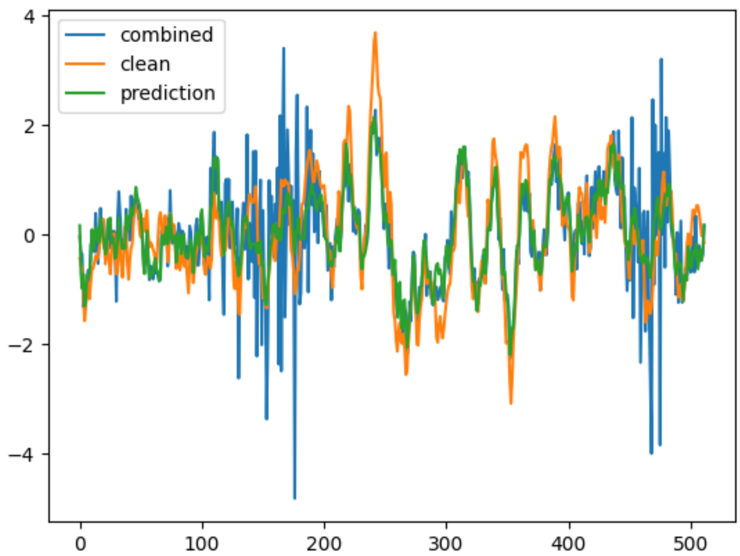

Figure 12: CNN 1 EMG

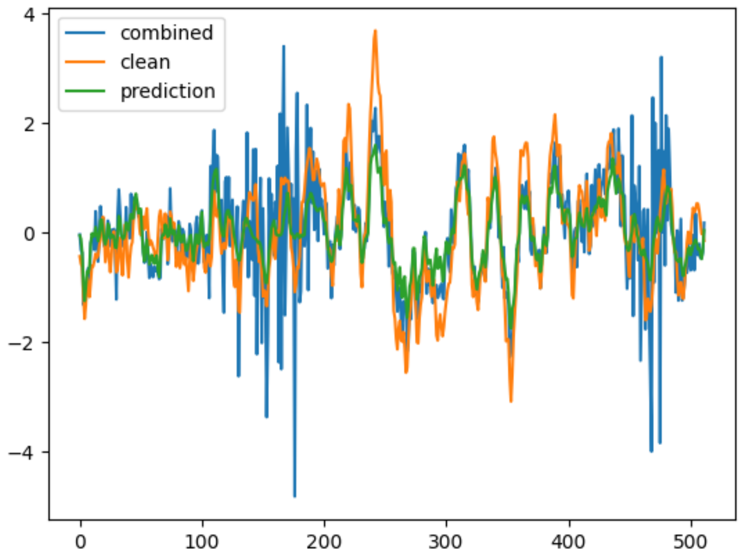

Figure 13: CNN 2 EMG

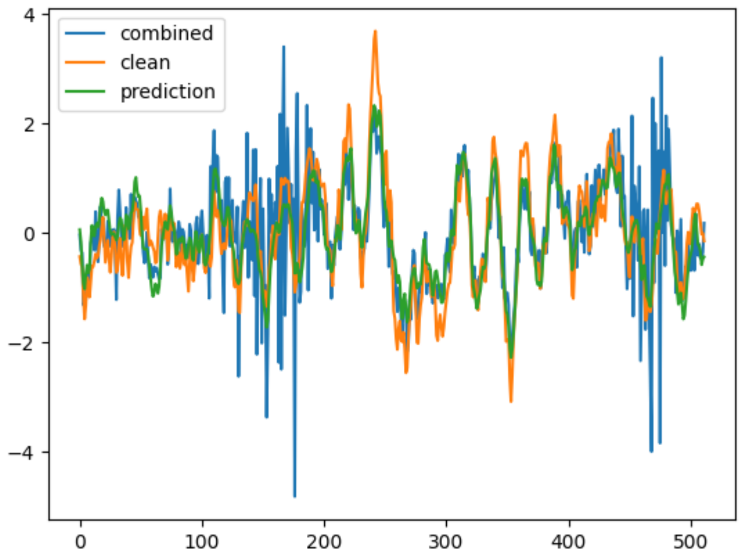

Figure 14: CNN 3 EMG

5 Conclusion

The paper explored the possibility of using deep learning for cleaning eeg data of artifacts. Multiple datasets and model types were explored resulting in a convincing win of convolutional neural networks.

References

[1] Miltiadous A, Tzimourta KD, Afrantou T, Ioannidis P, Grigoriadis N, Tsalikakis DG, Angelidis P, Tsipouras MG, Glavas E, Giannakeas N, et al. A dataset of scalp eeg recordings of alzheimer's disease, frontotemporal dementia and healthy subjects from routine eeg. *Data*, 8:95, 2023.

[2] Christoffer Hatlestad-Hall, Trine Waage Rygvold, and Stein Andersson. "srm resting-state eeg", 2022.

[3] Blair Kaneshiro, Duc T. Nguyen, Jacek P. Dmochowski, Anthony M. Norcia, and Jonathan Berger. Naturalistic music eeg dataset - hindi (nmed-h). Stanford Digital Repository, 2016.

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[5] Haoming Zhang, Mingqi Zhao, Chen Wei, Dante Mantini, Zherui Li, and Quanying Liu. Eegdenoisenet: a benchmark dataset for deep learning solutions of eeg denoising. *Journal of Neural Engineering*, 18(5):056057, oct 2021.