

# Prediction of Response Time and Vigilance Score in a Sustained Attention Task from Pre-trial Phase Synchrony using Deep Neural Networks

MASTANEH TORKAMANI-AZAR<sup>1</sup>, SUMEYRA KANIK<sup>1</sup>, SARA AHMED<sup>1</sup>, SERAP AYDIN<sup>2</sup>, AND MUJDAT CETIN<sup>1,3</sup>

<sup>1</sup>Signal Processing and Information Systems (SPIS) Laboratory, Sabancı University, Istanbul, Turkey

<sup>2</sup>Department of Biophysics, Faculty of Medicine, Hacettepe University, Ankara, Turkey

<sup>3</sup>Department of Electrical and Computer Engineering, University of Rochester, Rochester, NY, USA



HACETTEPE  
ÜNİVERSİTESİ



UNIVERSITY of  
ROCHESTER

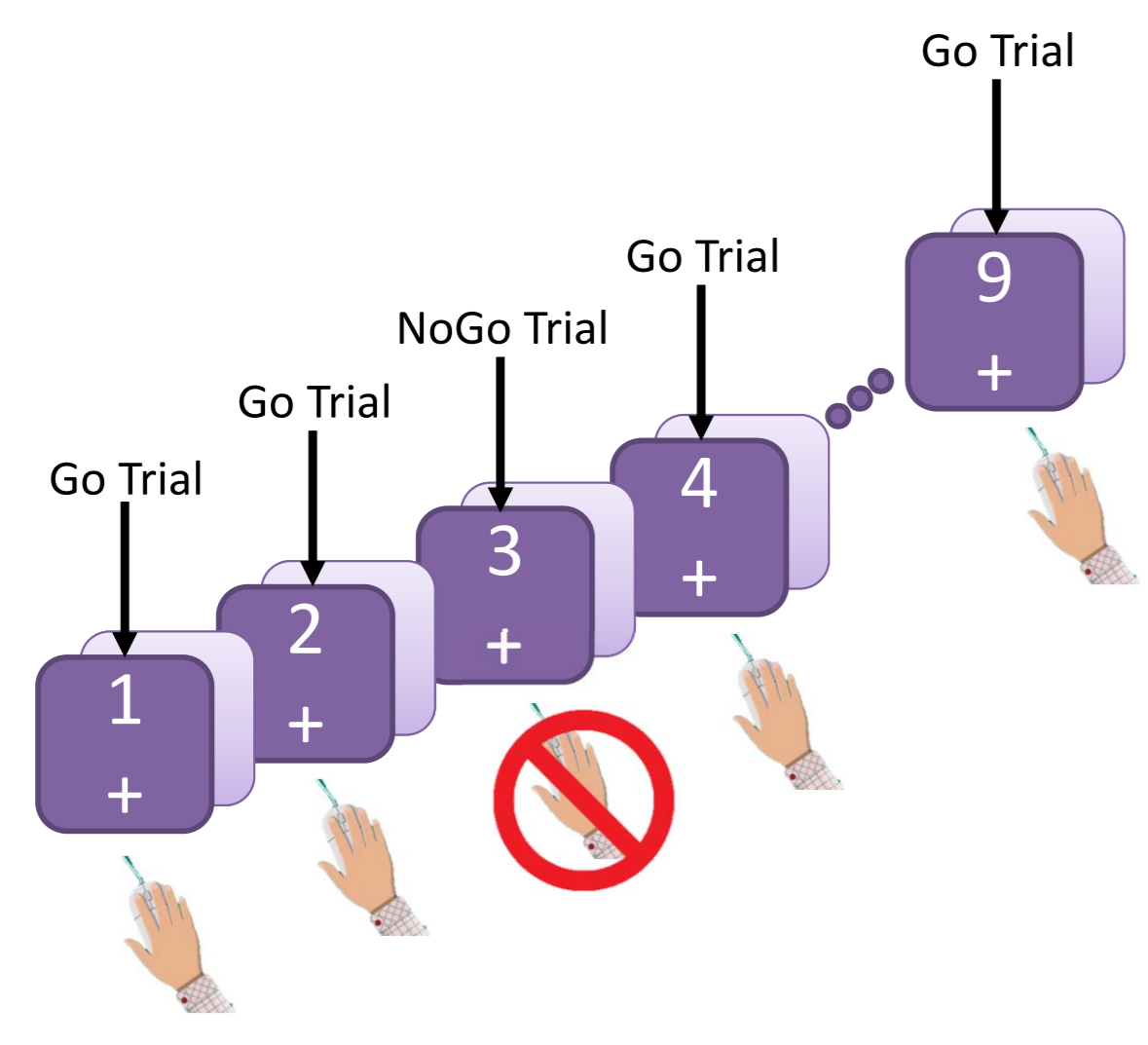
## MOTIVATIONS

- Assessment of vigilance is critical in long BCI experiments, ADHD diagnosis, air traffic monitoring, and long-haul driving.
- Current vigilance labeling methods are usually subjective or require facial videos.
- People demonstrate large differences in their response styles (accuracy-speed tradeoff) and the ability to maintain their performance levels.
- Spatial correlates of EEG signals are rarely used to *predict* continuous vigilance scores and response time in long experiments.

## CONTRIBUTIONS

1. Using Deep Neural Networks (DNNs) for modeling tonic vigilance scores in long sustained attention tasks from spatial relationships of EEG signals, and
2. Introducing an objective performance-based measure for vigilance labeling

## EXPERIMENT DESIGN



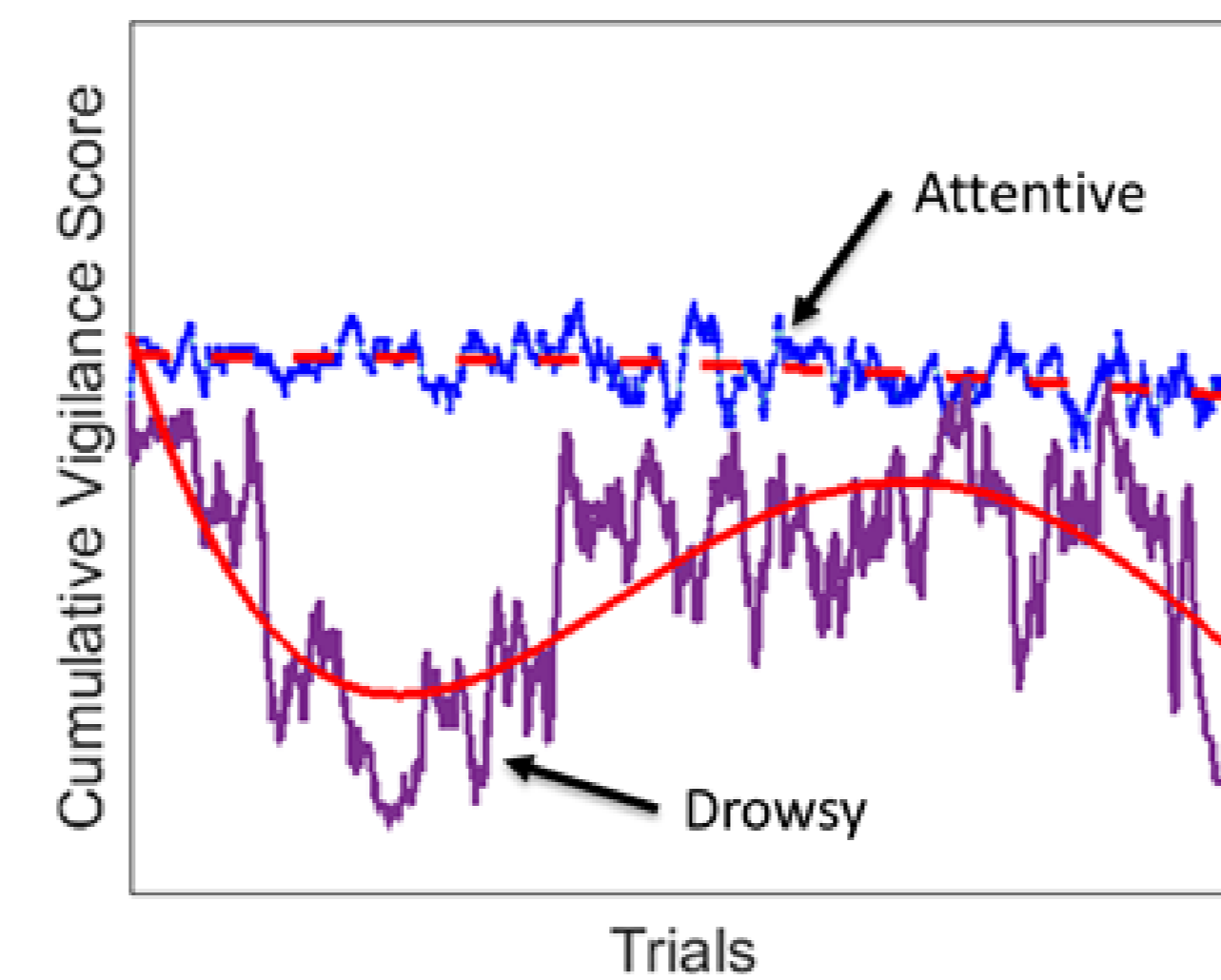
- Ten participants; average age  $30.25 \pm 6.95$  years
- Fixed-sequence Sustained Attention to Response Task
- 12 blocks of 225 digits (trials) with varying inter-stimulus intervals
- Task lasting for 105 to 110 minutes
- 64-channel EEG, Biosemi ActiveTwo system @ 2048 Hz
- Automatic artifact removal, back-propagation, and reconstruction:
  - Each block band-passed from 1 to 70 Hz,
  - Ocular artifact removed using linear combination of simultaneously recorded EOG signals, and
  - Using the Logistic infomax ICA algorithm, ICs removed if exceeding  $\pm 9$  SD from their mean.

## CONTACT INFORMATION

Webpage <https://linkedin.com/in/mastaneh-torkamani-azar/>  
Email [mastaneh@sabanciuniv.edu](mailto:mastaneh@sabanciuniv.edu)

## ADAPTIVE VIGILANCE LABELING

- Five-level Trial Vigilance Score (TVS)
  - TVS = 4 for correct double clicks and very fast and correct responses ( $RT < 50$  ms),
  - TVS = 3 for correct responses ( $RT < \text{lowerRT}$ )
  - TVS = 2 for correct responses with  $\text{lowerRT} < RT < \text{upperRT}$
  - TVS = 1 for wrong clicks, slow responses ( $RT > \text{upperRT}$ ), and for double click trials followed by a missed response.
  - TVS = 0 for single missed responses.
- $\text{lowerRT} = 250$  ms, and  $\text{upperRT} = \text{mean} + 2 \text{SD}$  of RT from the first 27 trials
- Cumulative Vigilance Score (CVS) obtained from a weighted moving average of 4 sequences ( $\sim 73$  seconds).



Comparison of CVS curves from different response styles

## PHASE SYNCHRONY INDICES

- Digit-locked epochs,  $[-200, 1,600]$  ms, downsampled to 512 Hz.
- Epochs band-passed to alpha, lower beta-1 and 2, mid-beta, upper beta, wide-band beta, and wide-band gamma.
- Averaging pairwise phase differences for all  $N = 225$  trials of a single block using Hilbert transform:

$$x_{HT}(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{x(t')}{t-t'} dt', \quad t \in \{1, 2, \dots, 923\},$$

$$\Phi_{ij}(t, n) = \Phi_i(t, n) - \Phi_j(t, n), \quad i, j = 1, 2, \dots, 64,$$

$$PLV_{bk}(t) = \frac{1}{N} \left| \sum_{n=1}^N e^{j\Phi_{ij}(t, n)} \right|, \quad N = 225.$$

- Block-wise features extracted from samples 1 to 103 in the pre-trial epochs, resulting in  $64 \times 64$  images:

$$PSI_{bk} = \frac{1}{T} \sum_{t=1}^T PLV_{bk}(t).$$

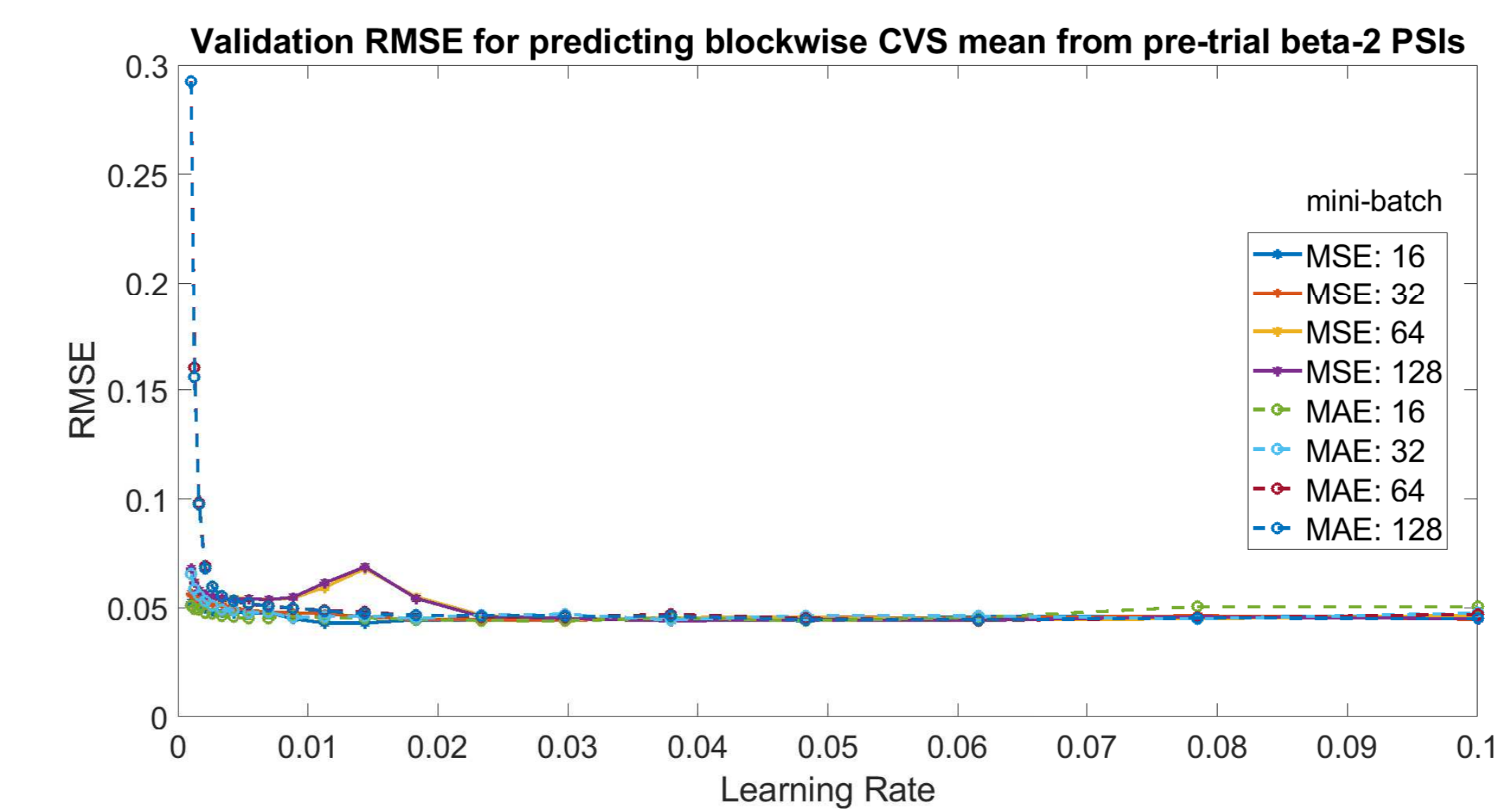
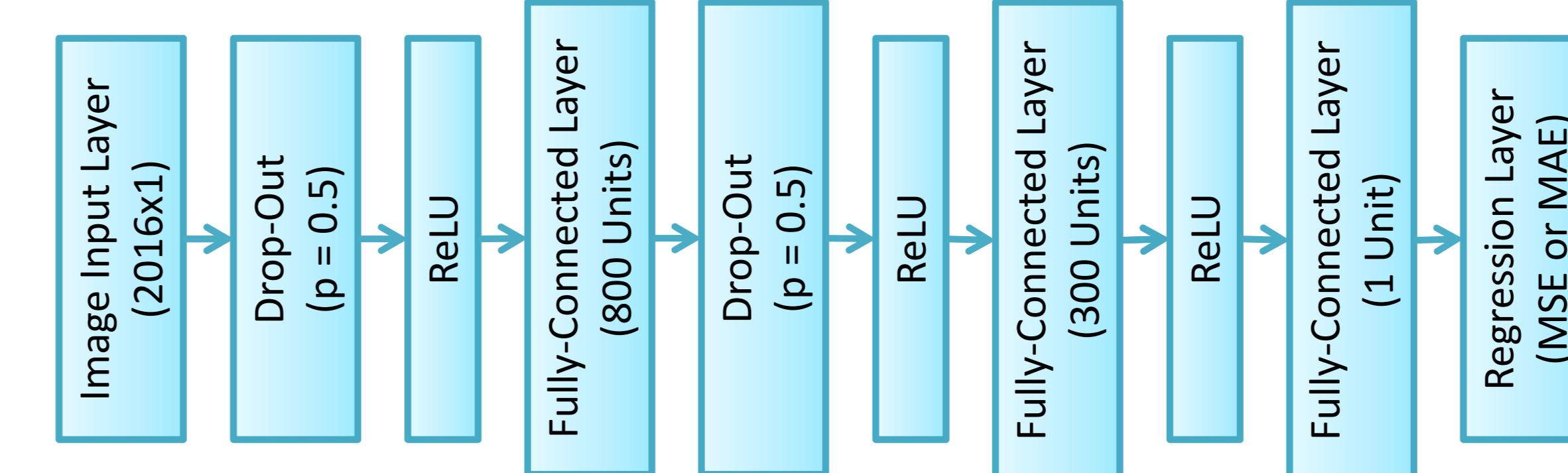
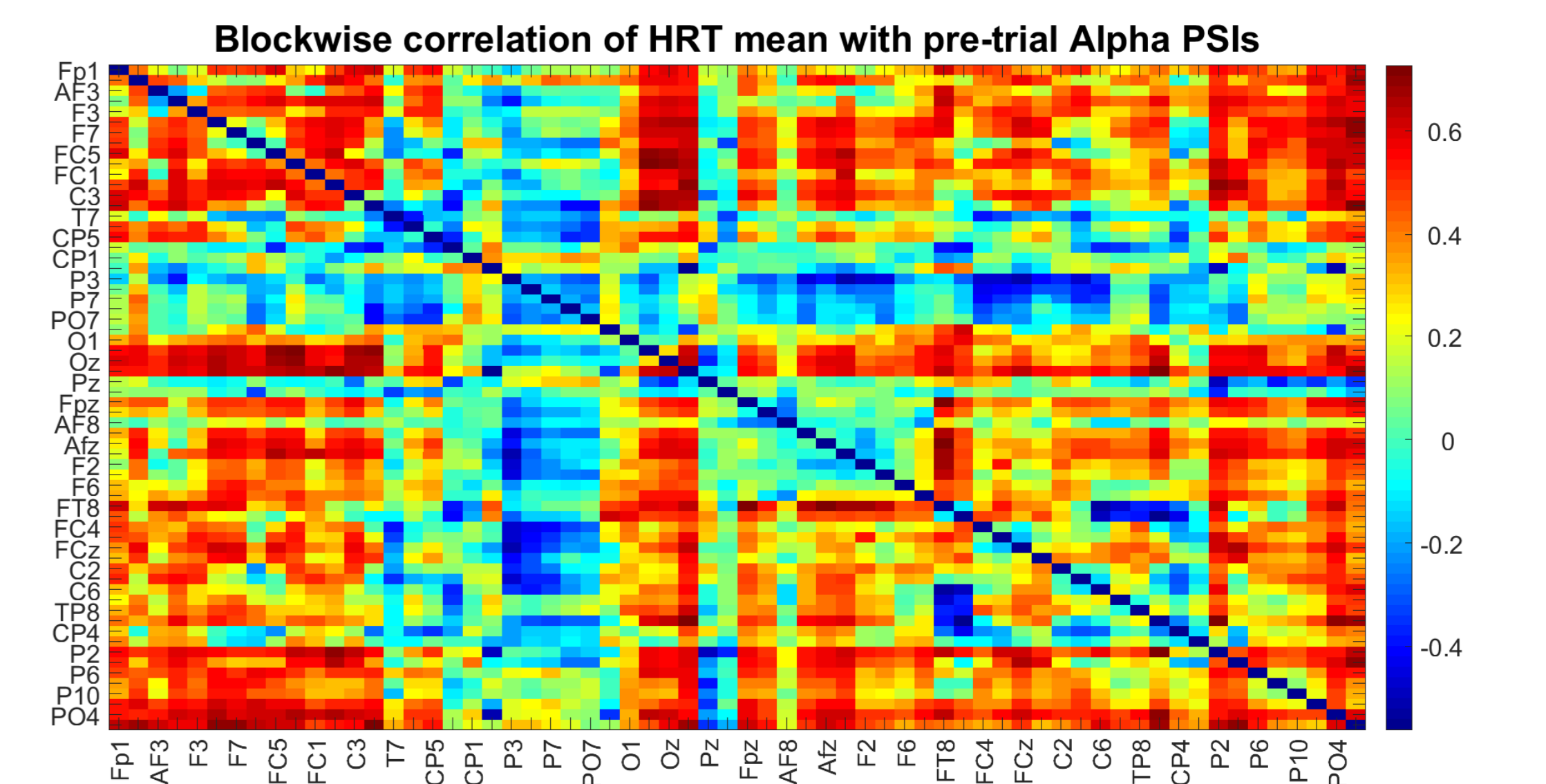
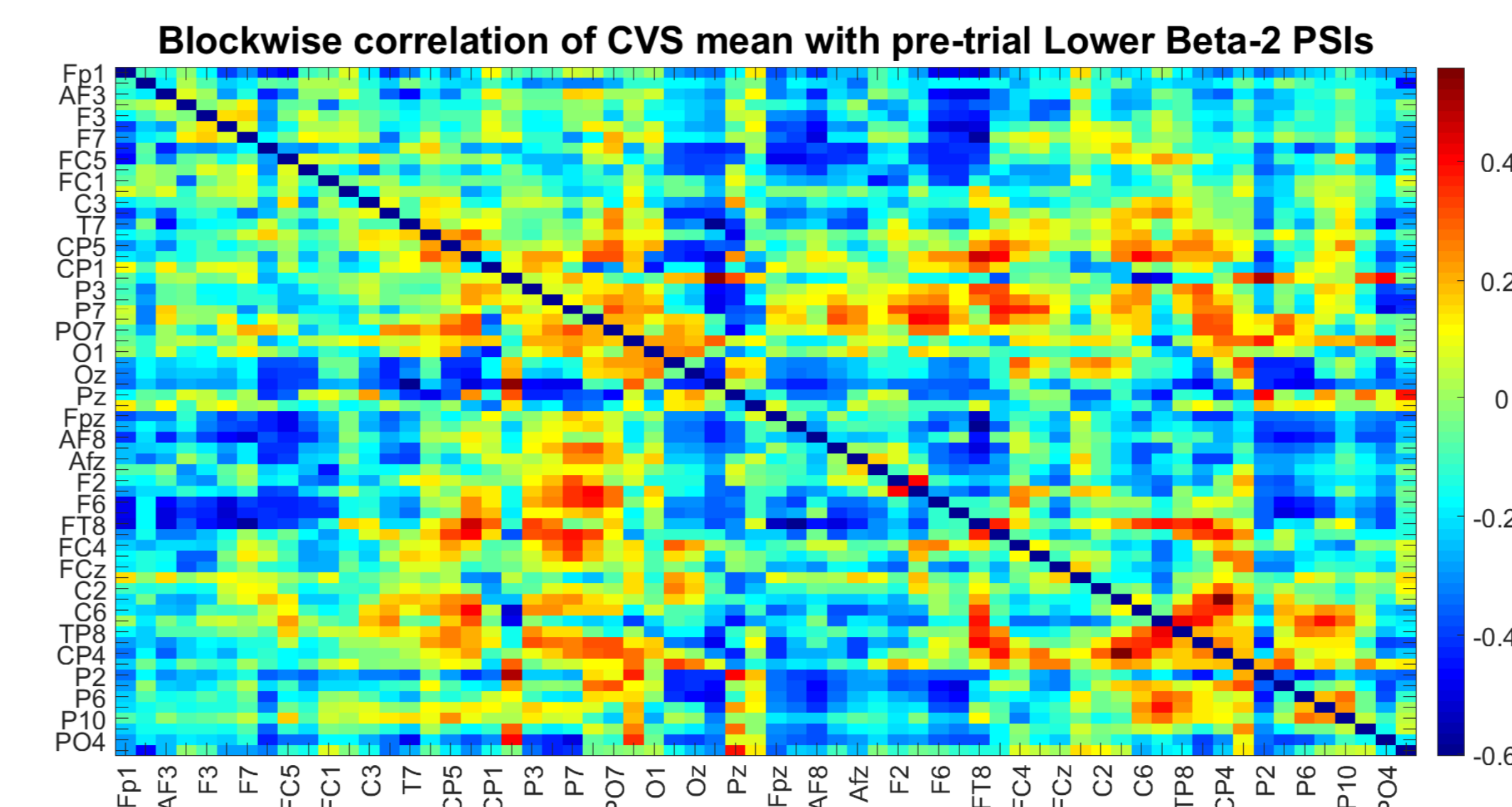
- Dataset  $X$ : 2016 unique values and 113 SART blocks.

## ACKNOWLEDGEMENT

This work is supported by the grant number 116E086 from the Scientific and Technological Research Council of Turkey (TÜBİTAK).

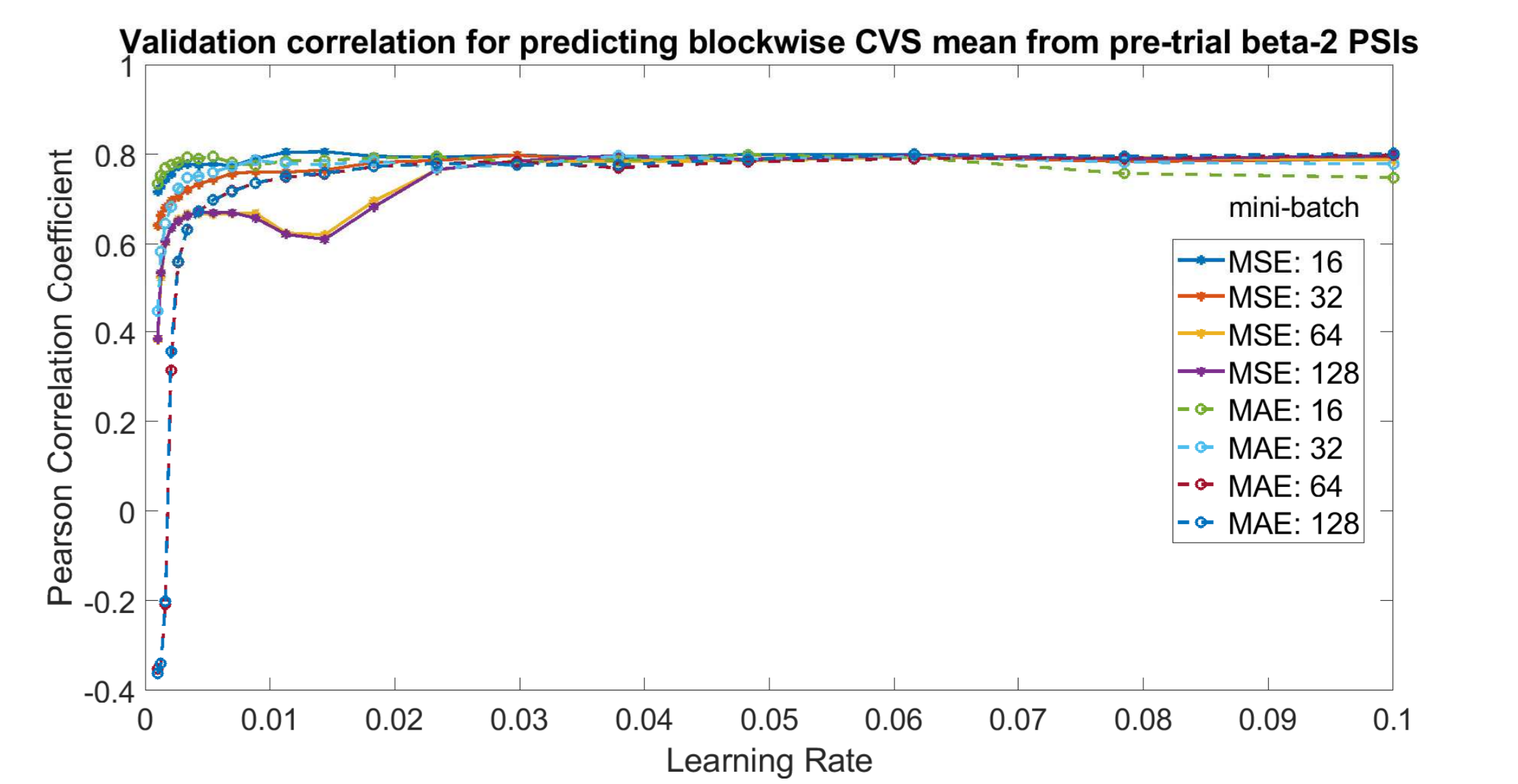
## REGRESSION WITH DNNs

- As a subset of neural correlates of pre-trial EEG, phase synchrony indices bear meaningful correlations with blockwise performance measures:



To predict block-wise CVS mean and hit response time mean from 7 frequency bands:

- Two cost functions utilized for regression: MSE and MAE
- Grid search for 20 learning rate values from 0.001 to 0.1 and mini-batch sizes of 16, 32, 64, and 128
- Networks trained for 5 runs and 4-fold cross-validation with stochastic gradient descent for 150 epochs



## CONCLUSIONS

- Stronger asynchrony in frontal cortex and from left centro-temporal with midline parieto-occipital, and synchrony within the right centro-tempo-parietal cortex are correlates of improved CVS.
- Alpha synchrony in the left fronto-central, with the right posterior channels, and within the right parieto-occipital cortex are strong correlates of delayed responses.
- Results are in line with roles of alpha and beta coherence in alertness to fatigue transition, attentional processes, and motor learning.

## ONGOING RESEARCH

- Development of multivariable regression models for prediction of overall performance scores in a long SART session from pre-task, resting-state EEG features
- Classification of drowsy versus alert states from trial-based spatio-spectro-temporal features using convolutional neural networks (CNNs)
- Modeling the temporal structures, prediction, and adaptation of vigilance scores using recurrent neural networks (RNNs)

## REFERENCES

- [1] W. Kong *et al.*, "Assessment of driving fatigue based on intra/inter-region phase synchronization," *Neurocomputing*, vol. 219, 2017.
- [2] Y. Sun *et al.*, "Discriminative Analysis of Brain Functional Connectivity Patterns for Mental Fatigue Classification," *Annals of Biomedical Engineering*, vol. 42, 2014.