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Real-time Visual Attention Training Through Closed-Loop EEG Neurofeedback

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Introduction

- Sustained attention refers to a cognitive capability to maintain focus during a task [1].
- Face-like visual stimuli undergo specialized processing in the human brain compared to non-face objects [2].
- The objective of the current work is to develop Python-based software for executing a neurofeedback visual attention training task.

Materials and Methods

1. Attention Training Paradigm

The paradigm includes three phases (eight blocks, 5 Seconds of text cue).

- Open loop pre/post-evaluation task
 - Target subcategory: Female/Male, Indoor/Outdoor.
 - Participants respond to the cue with a keypress.
- Closed-loop neurofeedback task:
 - Target category: Face, Scene.
 - Participants are instructed to focus on the cue.

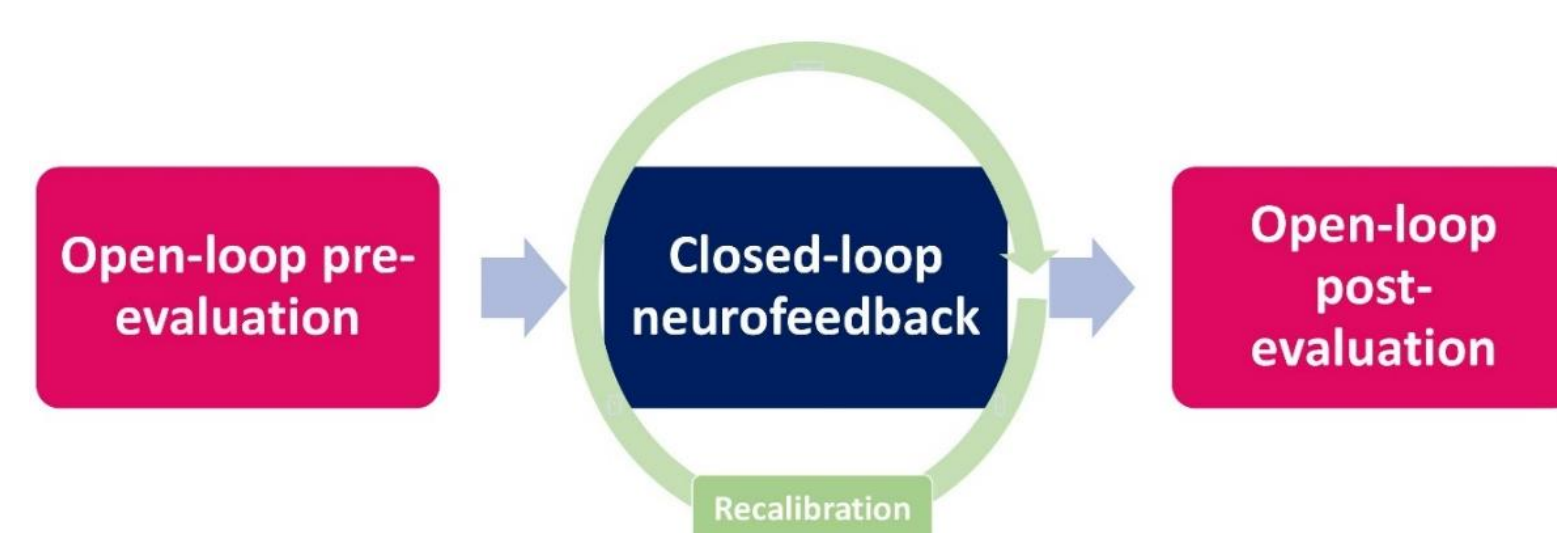


Fig.1 Attention training paradigm

2. Developed BCI Platform

- Wireless EEG headset (Unicorn Hybrid Black)
 - 250 Hz, 8 electrodes: Fz, FC1, FC2, C3, Cz, C4, CPz, Pz.
- Workstation computer with dual monitors
- Python-based software:
 - Data acquisition/analysis, neurofeedback training

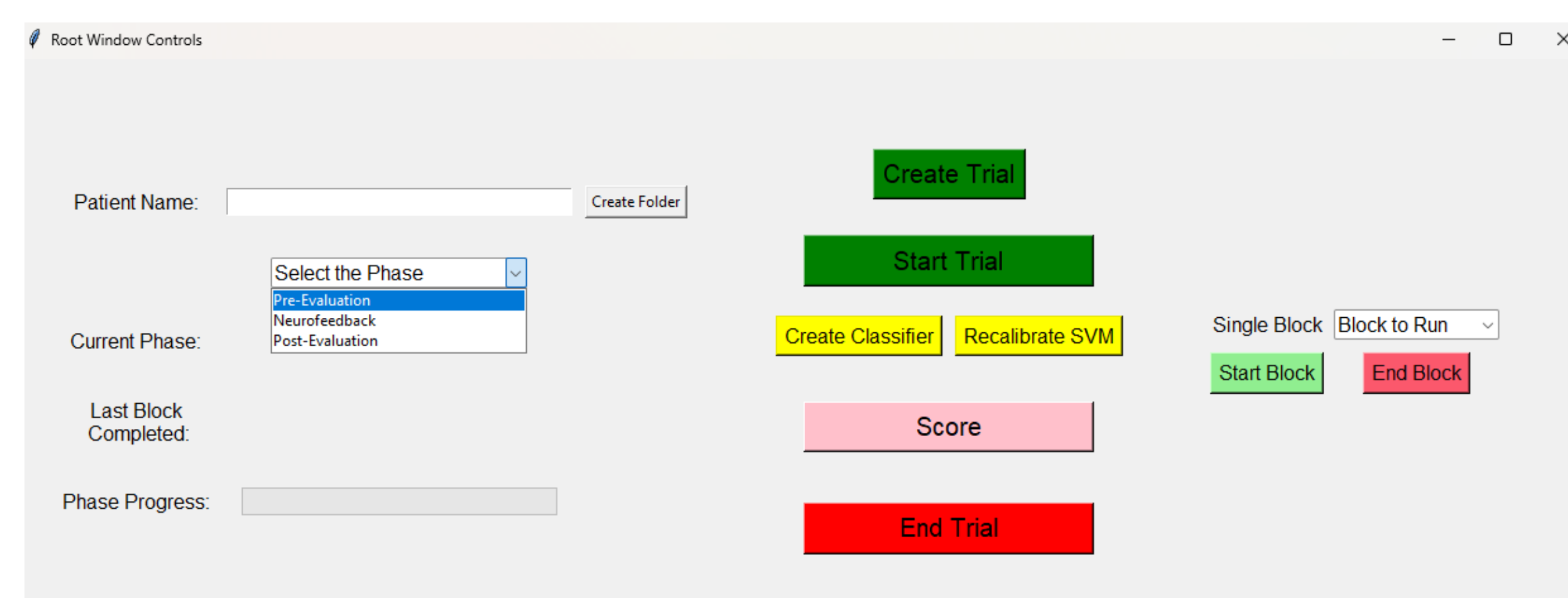


Fig.2 The developed GUI for the experimenter

3. Signal Preprocessing & Features Extraction

- Bandpass filtering (0.4 and 40 Hz), artifact rejection, & denoising.
- Segmenting data into 320 epochs, each containing 250 samples.
- ERP components: N180, P300, N500, N600, P700, and P900: (6x8).
- Decomposed EEG data into delta, theta, alpha, beta, and gamma bands.
 - Mean power: (5x8), Hilbert envelope: (5x8).
- Concatenated all features ([320, 8, 16], 90% training, 10% testing).
- Develop a linear SVM and MLP (optimize its parameters using Optuna).

4. Real-Time Neurofeedback Implementation

- A dynamic buffer for real-time EEG processing (5 seconds of data, size: (1250 x 8))
 - Data is appended every second, excess data beyond the 5-second is trimmed.
- A continuous and consistent bandpass filtering across buffers
 - Initial state is set by the first data; subsequent buffers use the previous buffer's final state, followed by artifact rejection and denoising.
- The most recent data chunk was used for feature extraction.
- The developed decoder using features predicts the individual's real-time attentional state.
 - Correct predictions increase image transparency; incorrect ones decrease it.
- Post-block: data added to the database collection, the model retrained, and a recalibrated decoder used for the next block.

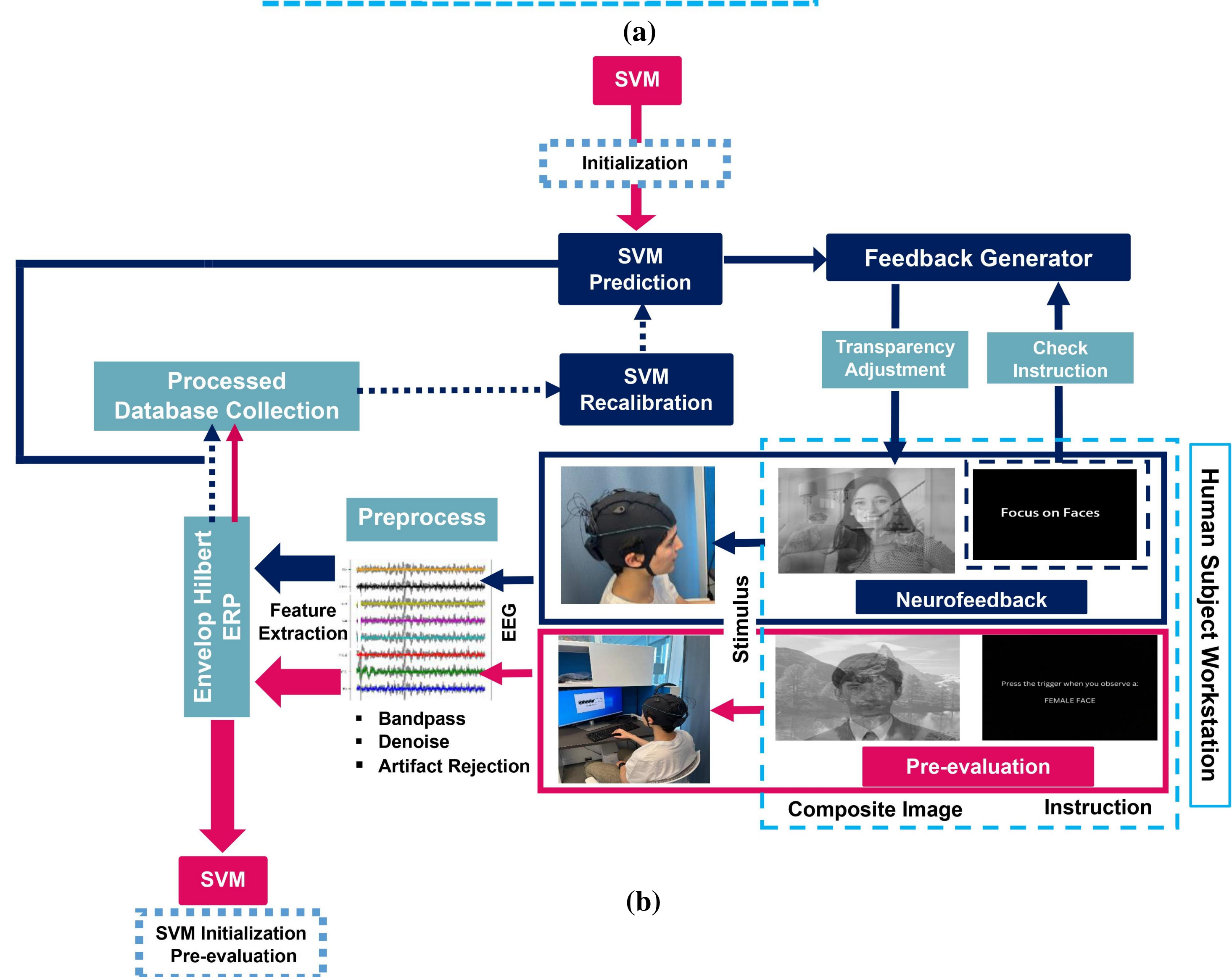
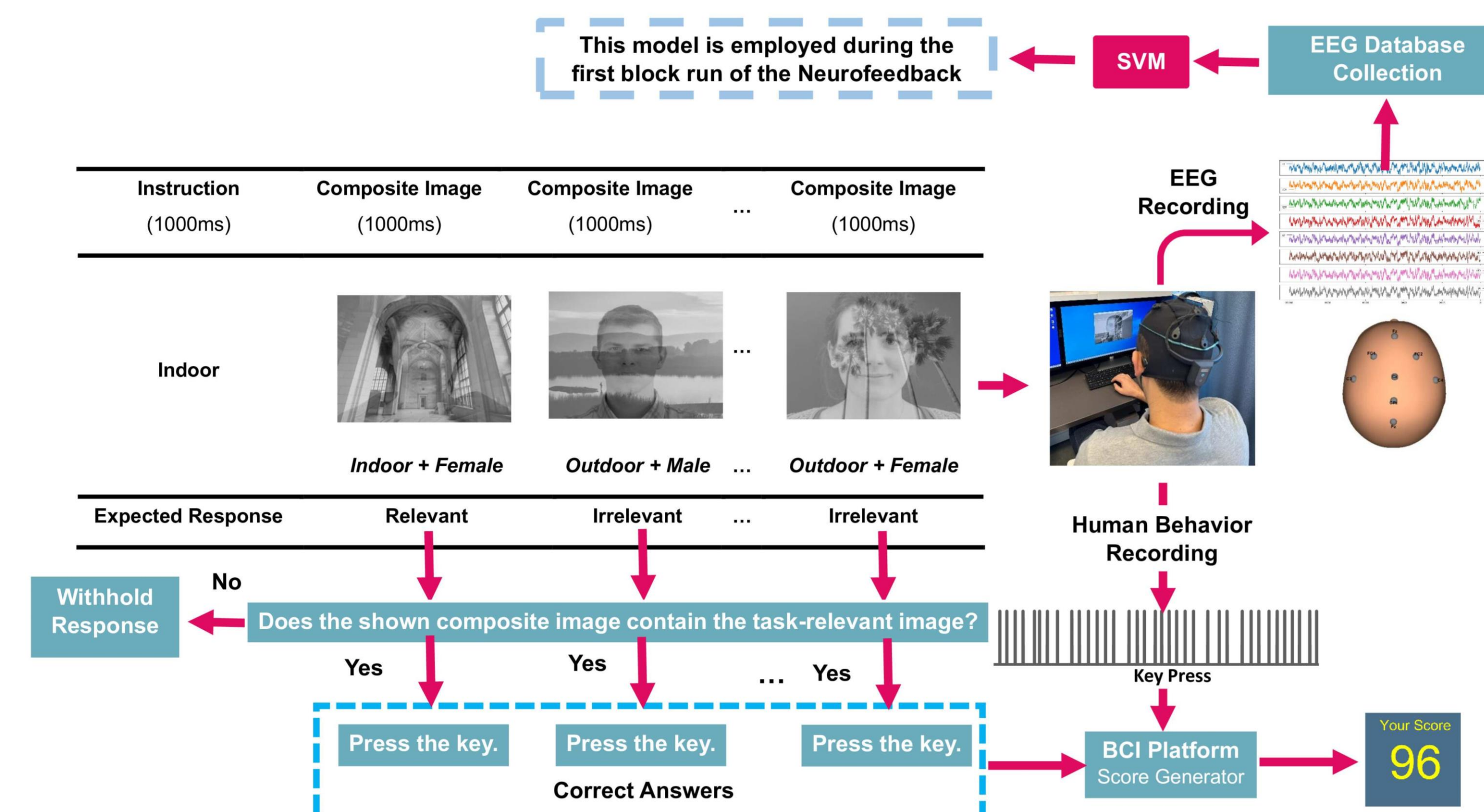


Fig.3 Developed BCI Platform for neurofeedback visual attention training, (clinical trial number: NCT05908253). (a) The pre/post-evaluation (offline/ open loop) phase has eight blocks, starting with a 5-second text cue, followed by 40 images at 50% transparency. Human responses are recorded, and an attention score is computed at the end of this phase, also, utilizing acquired EEG data, the initial SVM decoder is developed and used for the first block run of the neurofeedback phase. (b) The real-time neurofeedback phase comprises eight blocks, each starting with a 5-second cue, followed by displaying eight composite images, each lasting for 5 seconds. Initially, the transparency for each category in the composite image is set at 50% and is subsequently adjusted every second. After each block, the SVM model is recalibrated and is used for the next block

Results & Conclusion

1. Offline Analysis (open-loop)

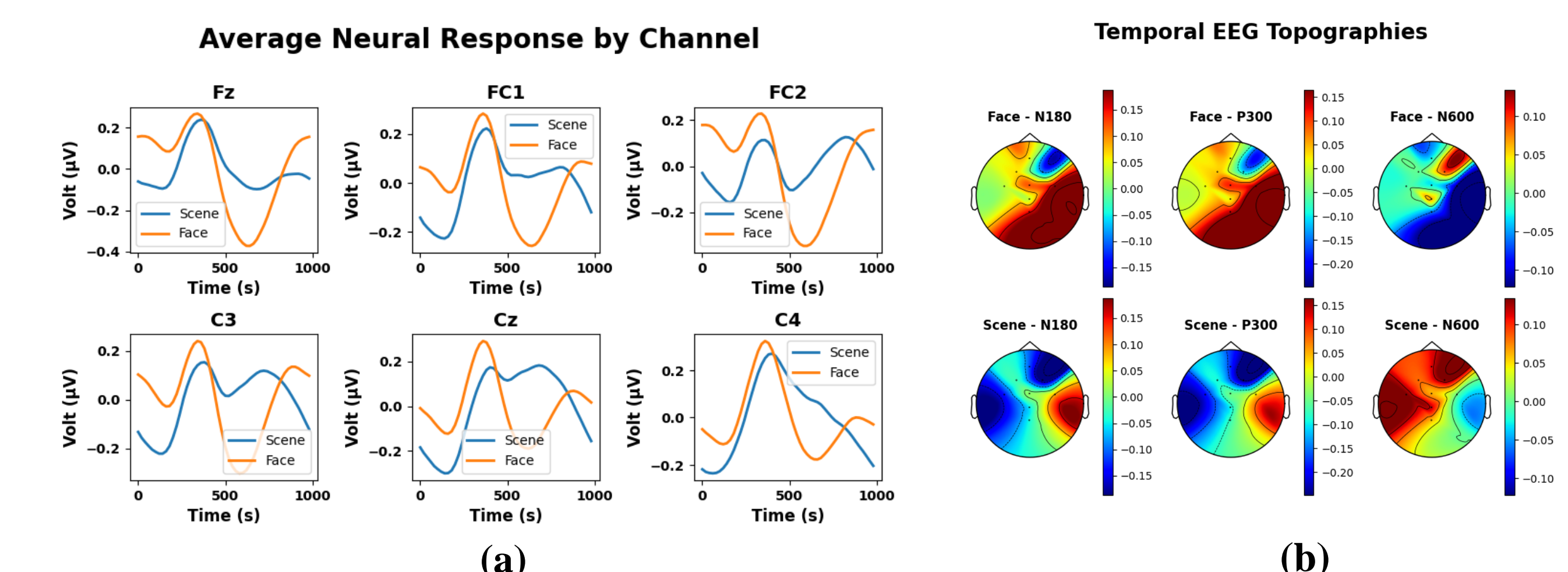


Fig.4 a) Average neural response to the stimuli: each epoch from 250 to 50 has been covered by averaging every five sequential data points, then, signals have been averaged across all blocks, producing a signal for each channel. b) Neural topographies for Face vs. Scene in selected temporal intervals

Table 1 MLP optimization across various subjects.

	S1	S2	S3	S4	S5	S6
accuracy	0.75	0.85	0.65	0.59	0.81	0.75
n_layers	1	4	3	3	1	2
n_units_layer0	329	114	414	258	210	194
n_units_layer1	-	247	355	176	-	311
n_units_layer2	-	461	285	62	-	-
n_units_layer3	-	173	-	-	-	-
activation	tanh	Relu	logistic	identity	Relu	tanh
learning rate	0.0032	0.0010	0.0103	0.04807	0.0019	0.0080
max_iter	518	605	69	946	863	240

Test Accuracy by Subject for MLP and SVM models

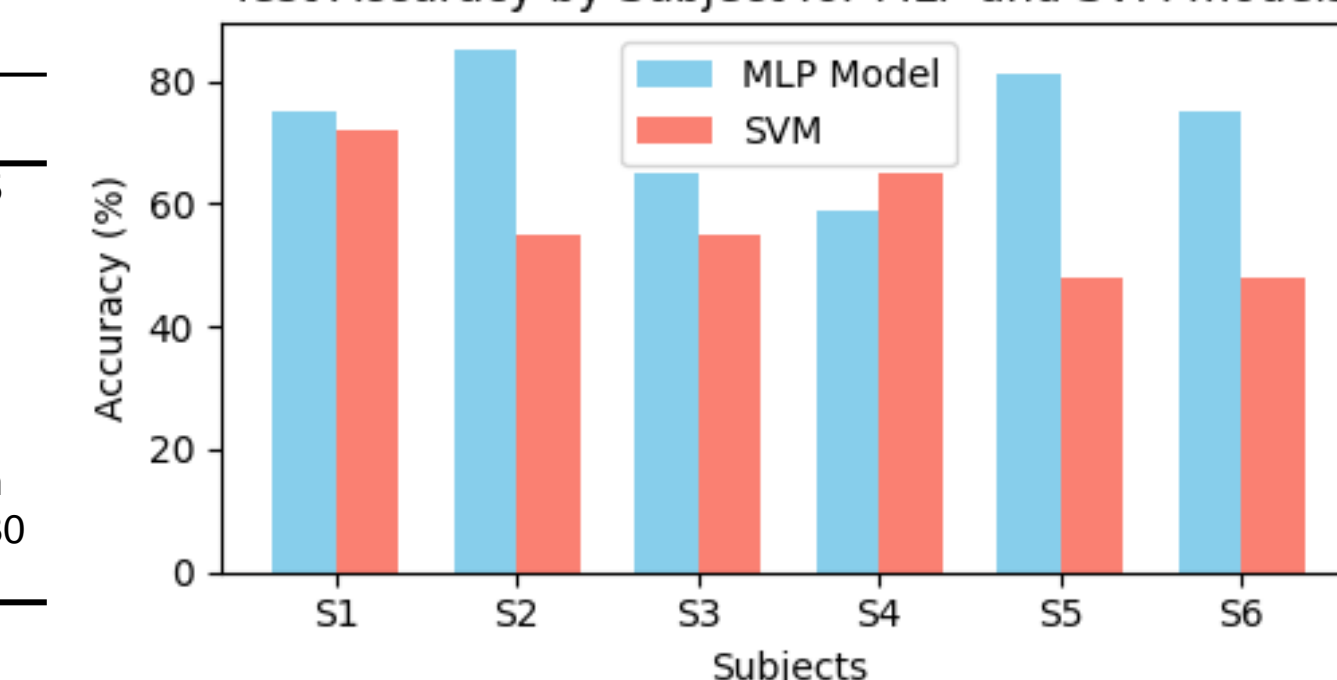


Fig.5 Comparison of the test accuracy between MLP and SVM

2. Closed-loop Neurofeedback Analysis (real time)

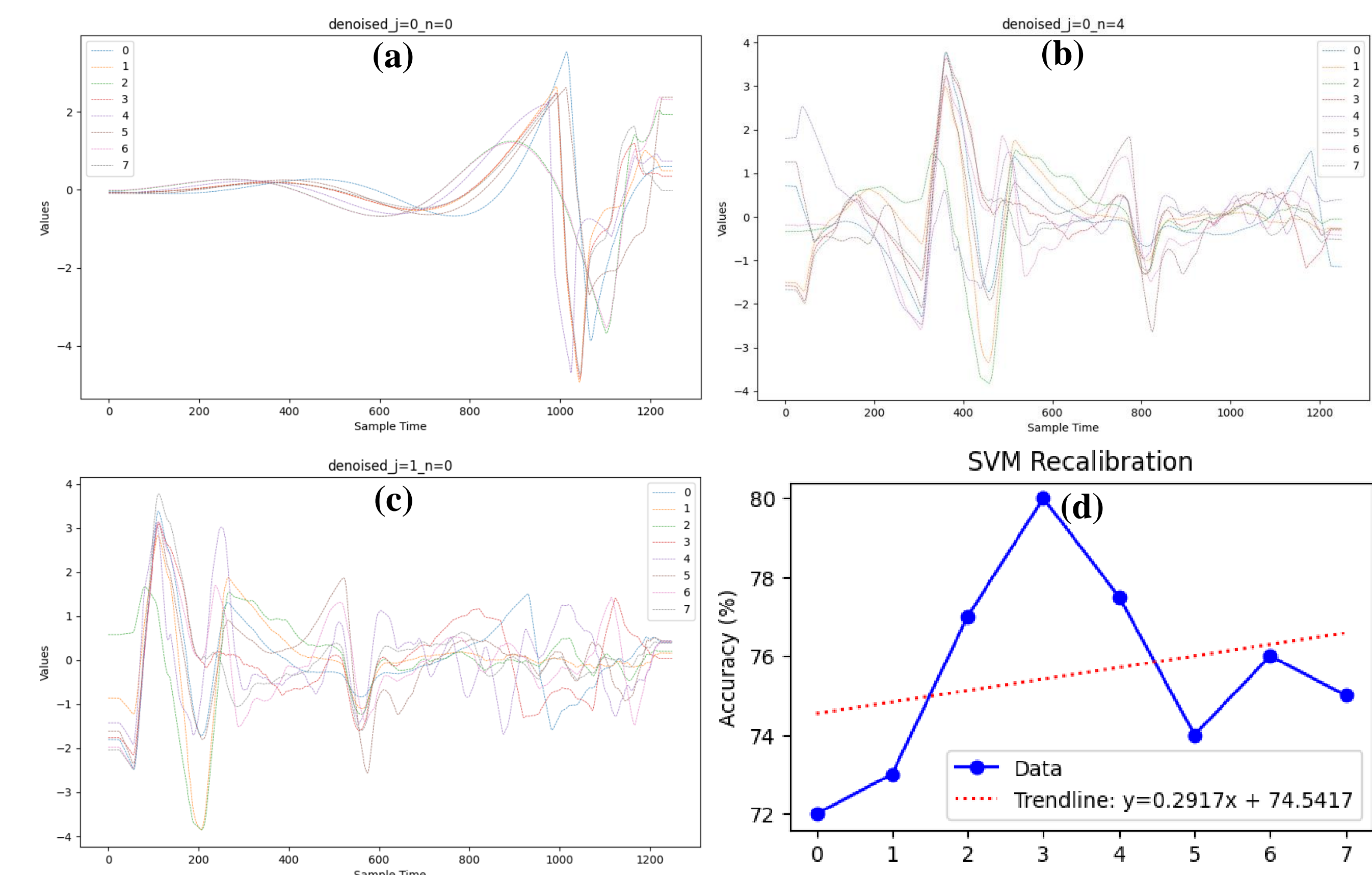


Fig.6 a-c) real-time denoising during the second and fifth chunks of data from the first image and the initial chunk from the subsequent image, respectively, d) Accuracy of recalibrated SVM vs. task progress

- Fig.6 (a-c) illustrates the efficacy of the dynamic buffer and filter's initial state in ensuring continuous preprocessing, even when consecutive data chunks diverge significantly in their neural signal characteristics (c).
- As depicted in Fig.6 (d) there is a positive trend in the SVM recalibration

References

[1] M. T. DeBettencourt, J. D. Cohen, R. F. Lee, K. A. Norman, and N. B. Turk-Browne, "Closed-loop training of attention with real-time brain imaging," *Nature Neuroscience*, vol. 18, no. 3, pp.470–478, 2015.

[2] Tuckute, G., Hansen, S.T., Kjaer, T.W. and Hansen, L.K., 2021. Real-time decoding of attentional states using closed-loop EEG neurofeedback. *Neural Computation*, 33(4), pp.967-1004.