Decoding the Mind: Neural Differences and Semantic Representation in Perception and Imagination Across Modalities.

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INTRODUCTION

Leveraging an extensive EEG dataset from multiple participants, we aimed to develop a robust model capable of generalizing across individual differences while accurately classifying EEG data into distinct cognitive states (perception vs. imagination) or semantic categories. In order to do so, we implemented a comprehensive signal processing protocol and feature extraction techniques, trained various machine learning and deep learning models, and assessed their effectiveness in decoding cognitive states (during the perception vs. the imagination tasks) or three semantic categories (i.e., flower vs. penguin vs. guitar).

Traditional machine learning models often struggle with overfitting and limited generalization, particularly when faced with the intricate nature of EEG signals. In contrast, deep learning architectures, specifically convolutional neural networks (CNNs), offer the advantage of capturing intricate features within high-dimensional data.

DATASET [1]

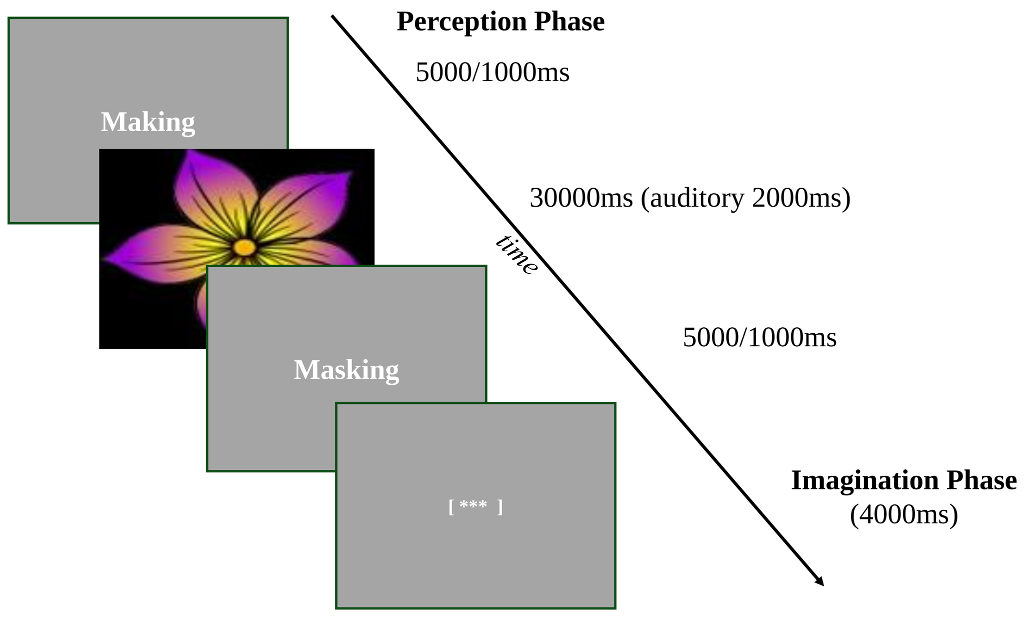

Figure 1: Experimental trail structure

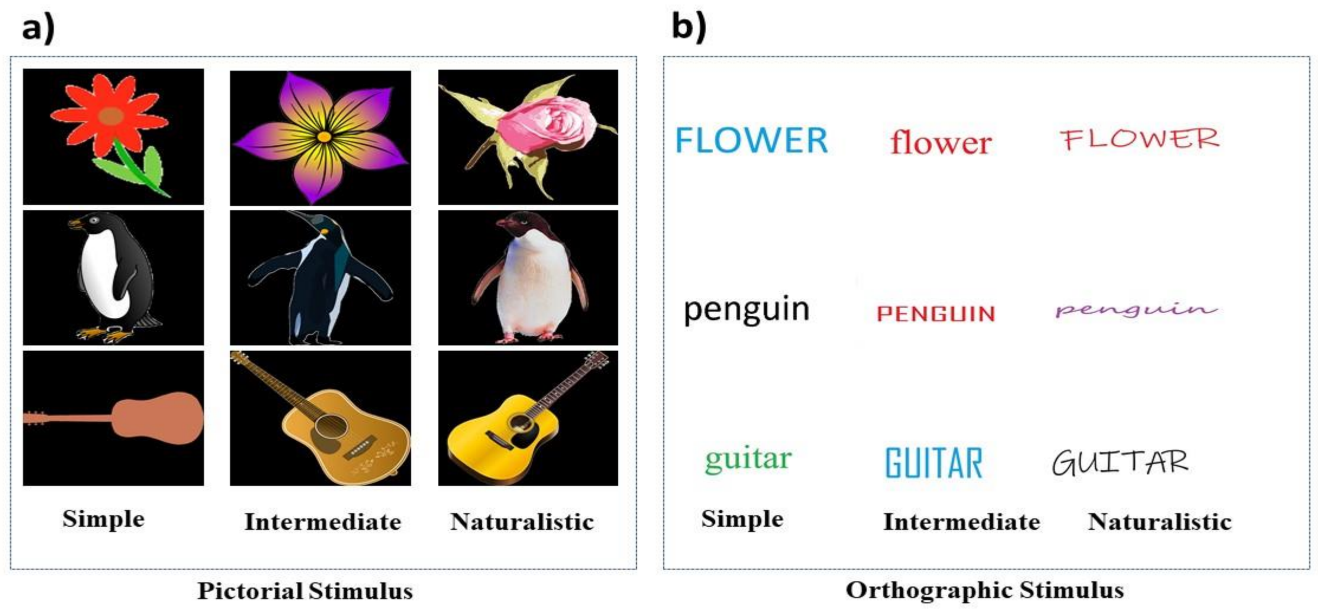

Figure 2: Pictorial(a) and orthographic(b) stimulus.

Table 1. No of trials by participants

Participant ID	Perception	Imagination	Total
sub-14	891	891	1782
sub-15	774	773	1547
sub-11	378	377	755
sub-03	450	450	900
sub-17	450	450	900
sub-08	450	450	900
sub-10	450	450	900
sub-16	450	450	900
sub-12	450	450	900
sub-19	315	315	630
sub-18	270	270	540

❖ **Total Trials: 11554**

SIGNAL PROCESSING AND MODEL ARCHITECTURE

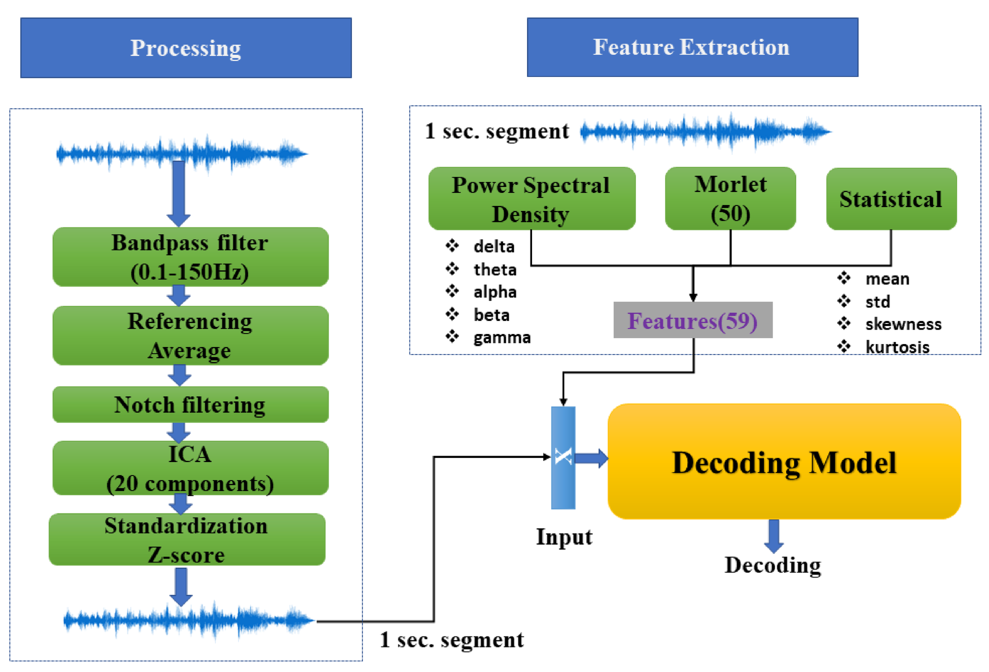

Figure 3: EEG Pre-processing Pipeline.

- ❖ **Bandpass Filtering**: Applied between 0.5 Hz and 150 Hz to eliminate low-frequency drifts and high-frequency noise.
- ❖ **Common Average Referencing**: Used to enhance spatial resolution across electrodes.
- ❖ **Notch Filtering**: Removed power line noise at 50 Hz and 100 Hz.
- ❖ **ICA**: Decomposed signals into 20 components to isolate neural sources and identify artifacts.
- ❖ **Z-Score Normalization**: Ensured amplitude consistency across the entire dataset.
- ❖ **Segmentation**: Data divided into 1-second intervals from stimulus onset for further analysis and model training.

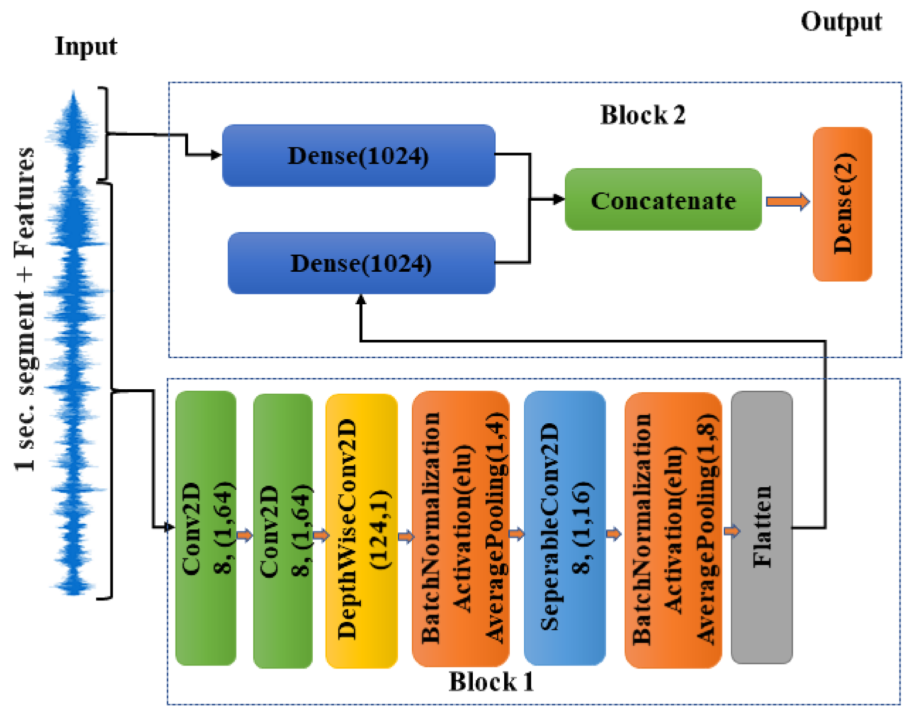

Figure 4: CNN Model Architecture.

Block 1 (Raw EEG Processing)

- ❖ Processes raw EEG data using **Conv2D**, **DepthwiseConv2D** and **SeparableConv2D** layers.
- ❖ **ReLU** Activation Functions: Add non-linearity to capture complex patterns.
- ❖ **Batch Normalization**: Stabilizes and accelerates training by normalizing outputs.
- ❖ **Average Pooling**: Reduces dimensionality while preserving essential features.

Block 2 (Feature Integration)

- ❖ **Flattening** and **Combining**: The output from Block 1 is flattened and integrated with features from Morlet wavelet transformations and statistical measures.
- ❖ **Dense Layers**: Two dense layers process the combined features to capture and integrate information effectively.
- ❖ Output Layer:
- ❖ Concatenates outputs from both blocks for decoding
- ❖ Training optimized with the Adam optimizer and sparse categorical cross-entropy loss.
- ❖ 100 Epochs: Training incorporates early stopping with patience of 5 to reduce overfitting.

RESULTS

PERCEPTION AND IMAGINATION DECODING

Table 2. Performance on aggregate data

Model Name	Train		Test	
	Accuracy	Loss	Accuracy	Loss
DeepConvNet	76.22%	0.46	74.78%	0.53
EEGNet	75.95%	0.49	75.56%	0.49
EEGNetSSVEPN	80.14%	0.42	76.08%	0.52
CNN (proposed)	77.48%	0.47	77.89%	0.48
Random Forest	100%	NA	68.85%	NA
SVC	100%	NA	51.21%	NA
XGB	100%	NA	50.77%	NA

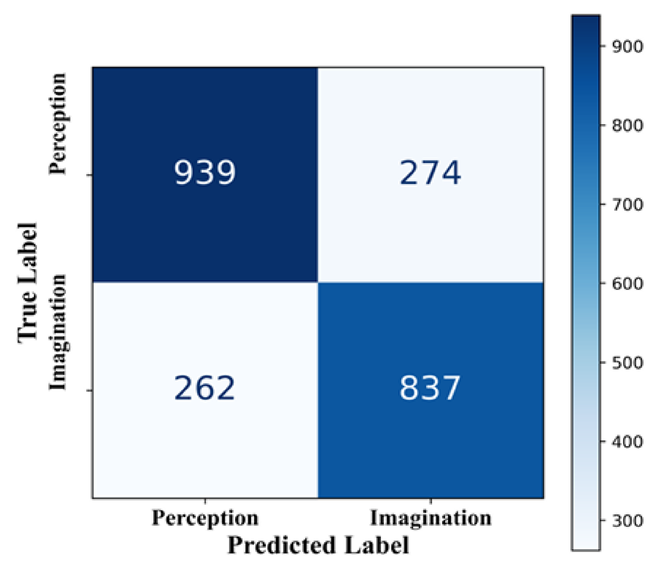

Figure 5. Confusion matrix

Table 3. Participant level performance

Model Name	Mean Accuracy	Standard Deviation
DeepConvNet	74.64%	10.15
EEGNet	75.26%	8.15
EEGNetSSEVPN	74.04%	8.42
CNN (Proposed)	76.82%	5.61

SEMANTIC DECODING

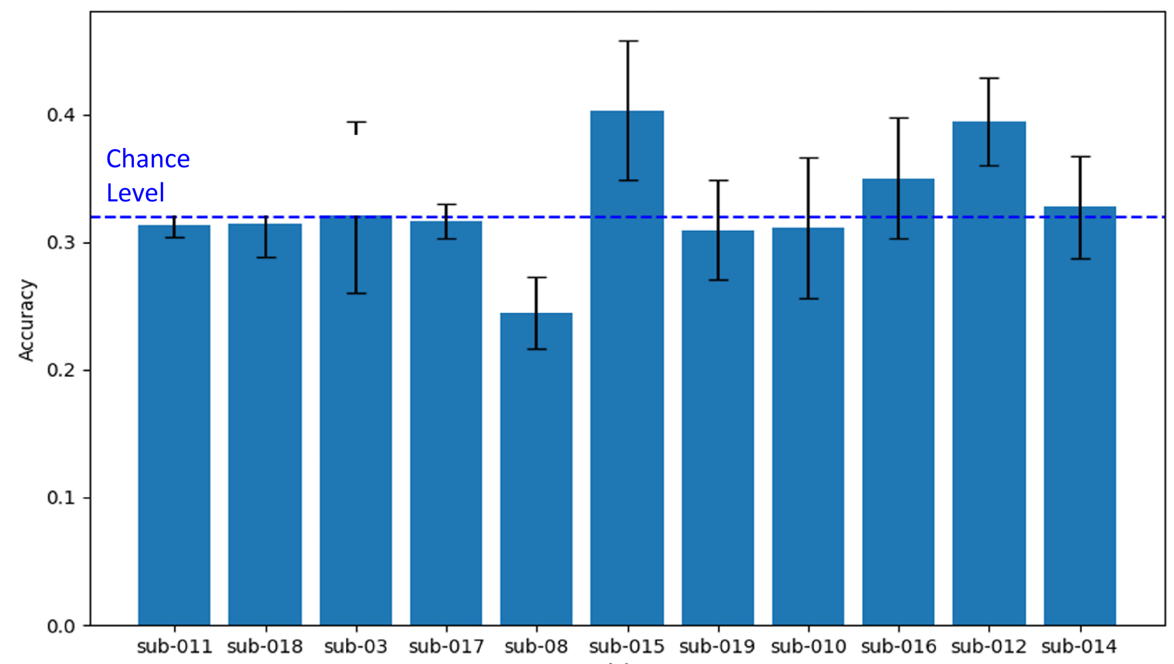

Figure 6. Subject level accuracy

Table 4. Comparison of model performance on semantic decoding

Model	Accuracy	Precision			Recall		
		Flower	Guitar	Penguin	Flower	Guitar	Penguin
DeepConvNet	35.42%	33.03%	36.01%	30.00%	18.23%	80.87%	0.43%
EEGNet	34.08%	34.10%	35.29%	0.00%	98.99%	0.72%	0.00%
CNN	36.03%	60.00%	35.98%	0.00%	0.38%	99.88%	0.00%
EEGNetSSVEPN	35.94%	100.00%	36.00%	30.56%	0.13%	98.56%	1.59%
RF	35.42%	33.03%	36.01%	30.00%	18.23%	80.87%	0.43%
SVC	33.78%	33.92%	32.74%	32.64%	88.23%	4.45%	6.80%
XGBoost	32.14%	34.20%	33.47%	29.14%	31.77%	29.96%	35.17%

CONCLUSION

❖ **Classifying perception vs. imagination cognitive states:**

- The proposed CNN-based model demonstrated superior accuracy and was participant invariant (test accuracy of 77.89\%), indicating robust generalization capabilities across all participants.
- In contrast, traditional machine learning models, including Random Forest, SVC, and XGBoost, exhibited significant overfitting, as reflected in their comparatively lower test accuracies.

❖ **Classifying semantic categories:**

- The Random Forest model displayed a balanced performance across various semantic categories, but none of the models achieved a classification that was above the chance level.
- This failure might be linked to the design of the experiment, where participants were asked to focus on the perceptual characteristics of the items instead of their semantic content.
- More research will help determine if these models improve when this variable is controlled.

REFERENCE

[1] H. Wilson, M. Golbabaee, M. J. Proulx, S. Charles, and E. O'Neill, "EEG-based BCI dataset of semantic concepts for imagination and perception tasks," *Scientific Data*, vol. 10, no. 1, p. 386, 2023.

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