Libet's Experiment: EEG-based Classification of Bistable Perception Neural Responses and Investigating the Impact of tACS on it

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Abstract

In this study, we investigated the neural responses of bistable perception using EEG signals and the potential effect of tACS stimulation on bistable perception. The participants were shown images of rotating cylinders and asked to identify the direction of rotation. EEG signals were recorded during the task, and the frequency of the alpha band and the gamma band were observed to change during perceptual switches. A tACS stimulation was applied in the gamma band frequencies to the area behind the head of the participant to investigate its effect on perception. The EEG data were pre-processed and subjected to feature engineering, and a Support Vector Machine(SVM) classifier was used to distinguish the epochs of perceptual switching and separate the times when the person was switching between the two states of perception. Next, using a mixed model based on the CNN decoder and a network of LSTM blocks, we achieved an accuracy of about 76% on the test data. The results showed that the tACS stimulation affected the perception of the participants, leading to faster perceptual switches. This study highlights the importance of investigating the neural responses of bistable perception and the potential use of tACS stimulation in modulating perception.

Bistable Perception | EEG | tACS | EEG-based Classification | VEP | Graph Analysis

Introduction

The relationship between brain signals and perception is a topic of ongoing research in neuroscience. Bistable images, in which the general physical characteristics of the stimulus are kept constant and a specific characteristic related to perception is changed, are a powerful tool for investigating this relationship. By recording brain signals while a person views bistable images, it is possible to investigate whether the brain signals can be used to predict a person's perception of the stimulus.

In this study, we used bistable images of rotating cylinders to investigate the relationship between brain signals and perception. Participants were asked to identify the direction of rotation (clockwise or counterclockwise) of the cylinder. By using advanced EEG analysis techniques, such as independent component analysis (ICA) and dipole source localization, this study aimed to identify the neural sources of the EEG signals and to study the temporal dynamics of the neural processes underlying perception.

The task was implemented using Psycho Toolbox and after pre-processing using the Makoto pipeline, the resulting data were subjected to feature engineering. The data was then tested using a Support Vector Machine (SVM) classifier to classify the subject's perception based on the brain signals.

This study aimed to investigate whether it is possible to classify people's perceptions according to the recorded brain signals and to understand the relationship between brain signals and perception. This study has the potential to provide new insights into the neural mechanisms underlying perception and contributes to our understanding of the neural basis of human cognitive function

Research Background

Overview. The relationship between brain signals and perception is a topic of ongoing research in neuroscience. Bistable images, in which the general physical characteristics of the stimulus are kept constant and a specific characteristic related to perception is changed, are a powerful tool for investigating this relationship. By recording brain signals while a person views bistable images, it is possible to investigate whether the brain signals can be used to predict a person's perception of the stimulus.

Previous studies have used bistable images to investigate the neural mechanisms underlying perception. For example, studies have used bistable images of rotating cylinders (1) and Necker cubes (2) to investigate the neural correlates of perception. These studies have revealed that the neural activity associated with perception is influenced by factors such as attention, context, and prior experience (1) (2). Also, another research shows that our perceptions of ambiguous objects can change even when visual stimuli and visual information is unchanged. Changes whose related processes take about 50 ms after stimulation, and the decision about the perceptual outcome has taken place at least 340 ms before the observer is able to indicate the consciously perceived reversal manually

Significance Statement

Previous studies have demonstrated the potential of using EEG signals to classify bistable perception in humans. These studies have focused on frequency features, spatial distributions, and event-related potentials (ERPs) to understand the relationship between brain signals and perception. By examining EEG signals during bistable perception, researchers have been able to identify changes in alpha and gamma band frequencies in the back of the head, which are believed to play a role in the perceptual switch. These findings highlight the importance of EEG in the study of bistable perception and the potential for further investigation into the use of EEG signals for the classification of human perception.

[1] All authors contributed equally to this work.

(3).
Based on the methodology used, previous works can be divided into two categories based on neuroimaging and EEG signal processing:

Neuroimaging: Recent studies have used neuroimaging methods, such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET), to investigate the neural correlates of perception in bistable images (1) (2). These studies have revealed that perception is associated with increased activity in a network of brain regions, including the primary visual cortex, the parietal cortex, and the prefrontal cortex (1) (2). However, these methods have limited temporal resolution and are not suitable for studying the dynamics of neural processes.

EEG: Electroencephalography(EEG) is a non-invasive technique that allows for the measurement of the electrical activity of the brain in real-time. It has the advantage of high temporal resolution, which is particularly useful for studying the dynamics of neural processes (4). Recent studies have used EEG to investigate the neural correlates of perception in bistable images. These studies have revealed that perception is associated with specific EEG patterns, such as the N2pc and the P3 components, that reflect the neural processes underlying perception (2).

Previous studies have used electroencephalography (EEG) to investigate the neural correlates of perception in bistable images. These studies have used various EEG analysis techniques, such as frequency analysis, spatial analysis, and event-related potential(ERP) analysis, to study the neural mechanisms underlying perception.

a. Frequency Analysis is used to investigate the oscillatory patterns of neural activity associated with perception. Studies have revealed that perception is associated with specific frequency bands, such as the alpha (5) and beta bands, that reflect the neural processes underlying perception (1) (2). For example, a study by Kornmeier and Bach(2004) used frequency analysis to investigate the neural correlates of perception in a bistable image of a Necker cube. They found that the alpha band activity was increased during the perception of one of the two possible interpretations of the image and decreased during the perception of the other interpretation.

b. Spatial Analysis is used to investigate the distribution of neural activity associated with perception. Studies have revealed that perception is associated with specific patterns of neural activity in different brain regions, such as the primary visual cortex and the parietal cortex (1) (2). For example, a study by (1) used spatial analysis to investigate the neural correlates of perception in a bistable image of a rotating cylinder. They found that the neural activity in the primary visual cortex and the parietal cortex was modulated by the direction of rotation of the cylinder.

c. ERP Analysis is used to investigate the temporal dynamics of neural activity associated with perception. Studies have revealed that perception is associated with specific patterns of neural activity that occur at specific time points after the presentation of the stimulus. These patterns are known as event-related potentials(ERPs)(6). For example, a study by Kornmeier and Bach(2004) used ERP analysis to investigate the neural correlates of perception in a bistable image of a Necker cube. They found that the N2pc and P3 components of the ERP were associated with the perception of the different interpretations of the image. The N2pc reflects the allocation of attention to the relevant features of the image, while the P3 reflects the update of the working memory representation of the image. Also, the analyzes in the P400 component also show significant effects during perception and under different stimuli. a study by Kornmeier, et al (7) shows this distinction in different traces of ERPs(dERPs).

These studies have used different EEG analysis techniques to investigate the neural mechanisms underlying perception in bistable images and have revealed that perception is associated with specific patterns of neural activity in different frequency bands, brain regions, and time points. The present study aims to use similar EEG analysis techniques, such as independent component analysis(ICA) (8) and dipole source localization, to investigate the neural mechanisms underlying perception in a bistable image of a rotating cylinder and contribute to our understanding of the neural basis of perception.

Classification: In the field of EEG signal classification, research by Alexander E. Hramov, et al (9) used an artificial neural networks architecture and achieved up to 95% accuracy in classifying EEG patterns corresponding to two different interpretations of the Necker cube. One of the highlights of this research was the presentation of a method that could be generalized and used well in various EEG signal classification tasks.

Stimulation. Bistable perception refers to the phenomenon where an ambiguous visual stimulus can be perceived as two or more different interpretations that switch spontaneously over time. The neural mechanisms underlying bistable perception are not yet fully understood, but it is believed that they involve interactions between multiple regions of the brain. In recent years, there has been growing interest in using transcranial alternating current stimulation (tACS) to modulate brain oscillations and investigate their role in bistable perception.

In a study by Cabral-Calderin, et al (10), the authors investigated the causal relationship between specific frequency band oscillations and perceptual reversals in bistable perception. The study used an ambiguous stimulus (the Structure-from-Motion, or SfM, stimulus) and applied tACS at alpha (10 Hz) and gamma (60 and 80 Hz) frequencies to participants while they performed the SfM task. The results showed a decrease in reversal rates when alpha tACS was applied, but no significant effect when gamma tACS was applied. This suggests that alpha oscillations may play a causal role in the initiation of spontaneous perceptual reversals in bistable perception.

Similarly, a study by Vossen, et al (11), found that the application of alpha tACS led to a decrease in perceptual switching rates in a bistable perception task. The study used a different bistable stimulus (the Necker cube) and applied alpha tACS (10 Hz) to participants. The results showed that the application of alpha tACS led to a reduction in perceptual switching rates, suggesting a causal role for alpha oscillations in bistable perception.

However, a study by Battaglini, et al (12) found conflicting results, with the application of alpha tACS leading to an increase in perceptual switching rates in a bistable perception task. The study used the same bistable stimulus as (11) (the Necker cube) and applied alpha tACS (10 Hz) to participants. The results showed that the application of alpha tACS led to an increase in perceptual switching rates, suggesting that the role of alpha oscillations in bistable perception may be more complex than previously thought.

A study by Ghiani, et al (13) investigated the effect of gamma tACS on bistable perception. The study used the SfM stimulus and applied gamma tACS (60 Hz) to participants while they performed the SfM task. The results showed that the application of gamma tACS led to a significant increase in perceptual switching rates, suggesting that gamma oscillations may play a role in modulating bistable perception.

Overall, the findings from these studies suggest a potential role for alpha and gamma oscillations in bistable perception. However, the results are not fully consistent and further research is needed to fully understand the neural mechanisms underlying bistable perception and the effect of tACS on these mechanisms.

It is important to note that tACS studies have a number of limitations and challenges, including the inter-subject variability in response to tACS, the limited understanding of the mechanisms of tACS, and the limited spatial resolution of tACS. Future research is needed to address these limitations and provide a more comprehensive understanding of the effect of tACS on bistable perception.

Another way to modulate brain oscillations is Transcranial direct current stimulation (tDCS), a non-invasive method that delivers low-amplitude (usually no more than 2 mA) over a short period (no more than 30 min) between electrodes (anode and cathode). The current is applied through at least one electrode to enter the brain and facilitate or inhibit spontaneous neural activities in the vicinity of the region (14).

First knowledge about the origin and mechanisms of cortical DC stimulation has been gained from animal experiments. In rats and cats, it was shown that applying an anodal DC stimulus to the surface of both the motor and the visual cortex increased cortical excitability and activity by depolarizing neuronal membranes at the subthreshold level, whilst a cathodal current resulted in the reverse effect, due to hyperpolarizing neurons(Andrea Antal, 2005).

In conclusion, while the role of alpha and gamma oscillations in bistable perception remains to be fully understood, the findings from these studies suggest that tACS may have potential as a tool for investigating the neural mechanisms underlying bistable perception. Further research is needed to confirm and extend these findings, but the potential implications for the understanding of bistable perception and the development of new therapeutic interventions are significant.

Results

Time Analysis. We made epochs of the signal from one second before switching to after that. Then we get the average of all these segments and plot the average evoked potential with all epochs (figure 1).

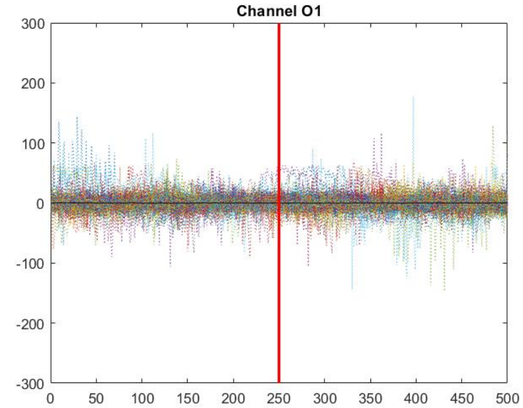

Fig. 1. Average Evoked Potential for channel O1

Spectral Power. Our findings imply that for the events in which the subject has chosen the right button, Pz and TP7 areas have more power spectral density and for the events in which the subject has chosen the left button, P4 and TP7 areas have more power spectral density.

Time-Frequency Analysis. We analyzed frequency changes over time by short-time Fourier transform of the signal. As you can see in figure 2, the power in some frequency bands increases in channel O2 before switching. Also, power increases after the switch in some frequencies in some channels (figure 2). As we know, when the subject perception changes, presses the key, just before the subject decision, some frequency power increases.

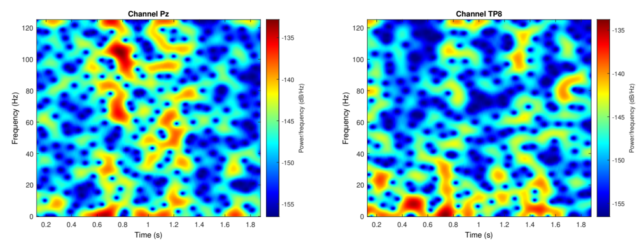

Fig. 2. Short-time Fourier transform

Functional Connectivity. To calculate the phase synchronism between the signals of each channel, consider the 2s epochs, in which the switch time is in the middle of it. Figure 3 shows the PLV relationship matrix between channels in different frequency bands. Also, a trial in which the subject sees clockwise rotation separate from the counter-clockwise.

Graph Analysis. Functional connectivity obtained from EEG data is represented by an undirected PLV graph $G = (V, E)$, vertices represent electrodes. Since weak PLV may represent spurious connections, we only consider PLV with values above a significance threshold (median of channels median). PLV above the threshold are represented by edges, whereas PLV below the threshold are ignored (figure 4) (15).

A. Clustering Coefficients for Unweighted Networks. Since this part, we calculate some features for our graph. Because the clustering coefficient is a major index that is used to assess the segregate function of networks, we examined whether our clustering coefficients change in different frequencies. As you see in figure 5, the average is higher in the alpha band but there is no significant difference in the alpha, beta, and gamma bands. Also, the statics parameter is almost the same in the right and left epochs.

B. Global Efficiency for Unweighted Networks. As same as clustering, the global efficiency is used for the unweighted PLV

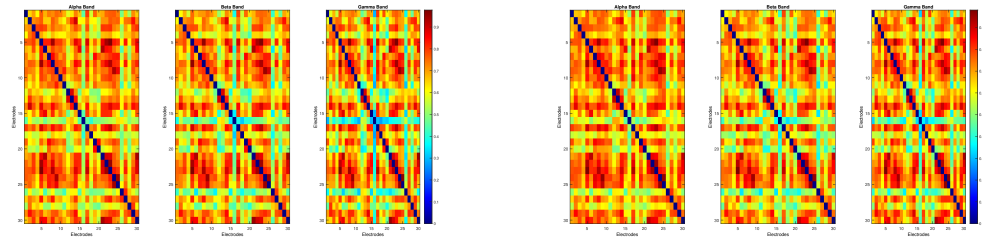

Fig. 3. Phase lock value between channels in alpha, beta, and gamma bands clockwise-anticlockwise trials.

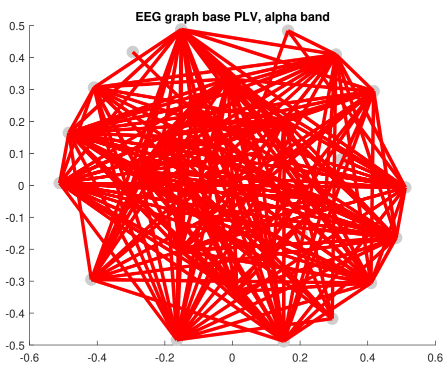

Fig. 4. Alpha band PLV graph. Edge with PLV lower than PLV median is removed.

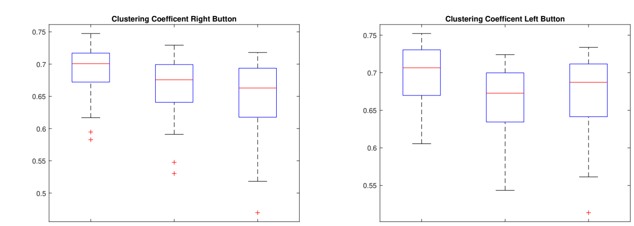

Fig. 5. Clustering Coefficient all channels alpha, beta, gamma band left button vs right button

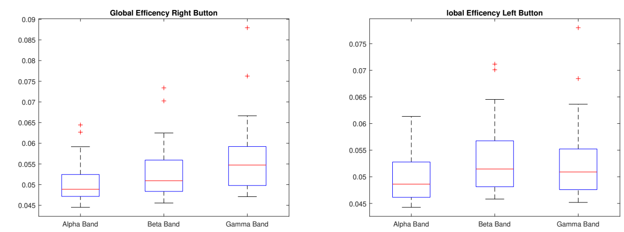

Fig. 6. Global Efficiency all channels alpha, beta, gamma band left button vs right

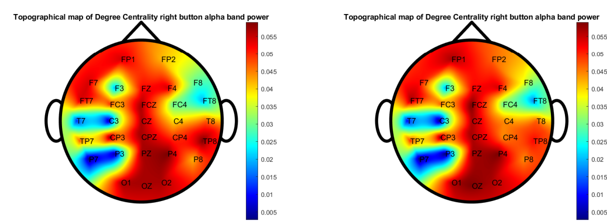

Fig. 7. Degree Centrality left button vs right alpha band

graph. The average is higher in a beta band. There is almost no difference between the two states of perception (figure 6).

C. Centrality for Unweighted Networks. Centrality is a biomarker for some illnesses. It shows the important region in the brain which has more connection and play important role in information transformation. The presence of high-closeness nodes in the occipital may represent hubs and the key role of this region in our task. Also, based on Betweenness-centrality, left central has more score either in a right switch or left. (figure 7-12)

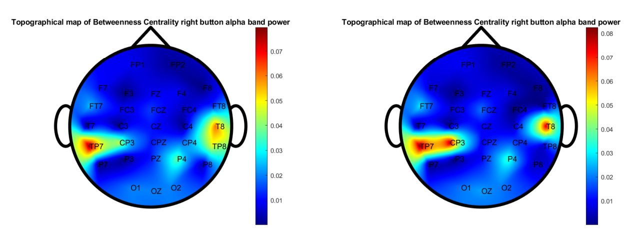

Fig. 8. Betweenness Centrality left button vs right alpha band

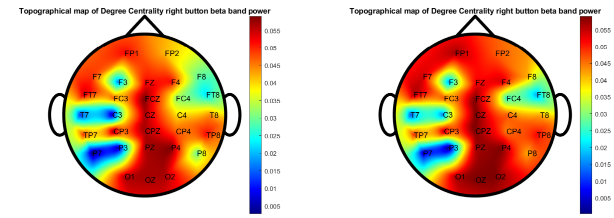

Fig. 9. Degree Centrality left button vs right beta band

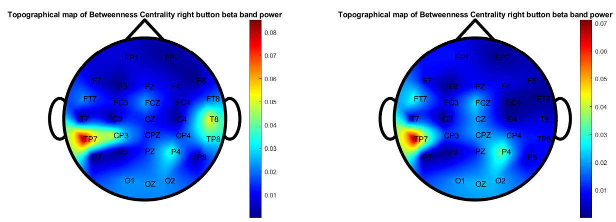

Fig. 10. Betweenness Centrality left button vs right beta band

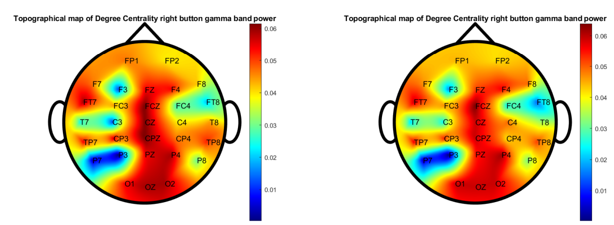

Fig. 11. Degree Centrality left button vs right gamma band

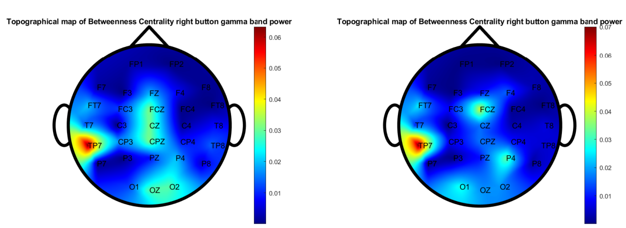

Fig. 12. Betweenness Centrality left button vs right gamma band

Discussion

Perception is strongly affected by the intrinsic state of the brain, which controls the propensity to either maintain a particular perceptual interpretation or switch to another. Lots of research has been done to find out the relationship between cognitive and EEG signal changes, For example is claimed that the occipital cortex is the primary visual area of the brain. It has different groups of neurons that separately encode color, orientation, and motion information.

In the previous sections, we analyzed EEG signals of perception tasks differently. In *Time Analysis* we obtained an average evoked potential near zero that does not give much information. The reason could be subject to delay. When the subject senses a switch in rotating, they press the proper key immediately, but with a delay. This various delay from epoch to epoch could spoil Evoked Potentials because of time shift. Also, the signal power of some electrodes in some frequencies band near the switch. As we show, there is no significant change in the graph feature between two right or left perception states, even the location of the hubs. We want to compare the brain network connectivity before and after tACS, but we have a limitation to getting EEG two times. Most of our results show P4, Pz, TP7, O2, and Oz electrodes, and their related brain zones and totally occipital region have a key role in our task.

In *Spectral Power* we obtained a promising difference in left/right epochs. For the events in which the subject has chosen the left button, P4 and TP7 areas are more active.

Then we analyzed *Time-Frequency* methods such as STFT and found that power in some frequencies in channel O2 increases before switching.

Lastly, the impact of a single-subject experiment could be slightly different from average, but not completely. In this case, we hope to perceive the same results in a larger population.

Materials and Methods

Subject. For both *Perception Task* and *tACS Task*, the subject was a twenty-two-year-old man with normal vision and familiar with the concepts of the tasks.

Perception Task. Using *Psychtoolbox*, we designed a task in which a bi-stable stimulus is shown on a screen, and the subject is requested to decide whether the cylinder is rotating clockwise or counter-clockwise and report it with proper buttons. As the bi-stable stimulus, we used a 2D movie consisting of points moving leftward or rightward, which due to depth perception it may seem like a rotating cylinder (see figure 13). The task consists of 3 blocks. Each block includes 50 trials of length 20 seconds (see figure 14). Simultaneously, we record a 30-channel EEG signal and save the exact time when the subject realizes a switch in the rotating, and presses the corresponding key. In order to avoid exhaustion, the subject is free to have a brief rest between trials.

EEG Recording. Subjects were seated in a quiet room. 30 EEG electrodes were placed according to the international 10–20 system. Two reference electrodes were placed on the left and right hemispheres (occipital lobe). EEG data were collected with a sampling rate of 250 Hz.

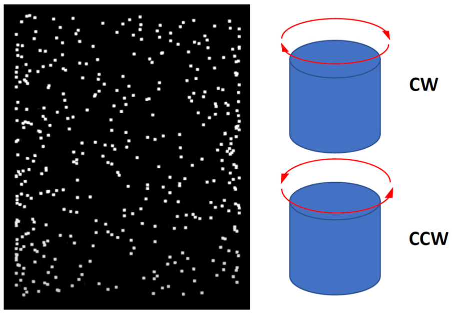

Fig. 13. The bistable perception; could be perceived clockwise or counter-clockwise

EEG Signal Preprocessing. In the preprocessing stage, the Makoto pipeline (Okamoto, M., Delorme, A., Makeig, S., & Lee, T. W. (2004). Automated classification of single-trial EEG: towards brain-computer interfacing. Journal of neuroscience methods, 134(1), 9-21.) was used to pre-process the EEG data before further analysis. The pipeline includes a series of steps that help to improve the quality of the data and make it more suitable for analysis. These steps were applied using the *EEGlab MATLAB* toolbox.

1) Firstly, the data were band-pass filtered between 1-Hz and 49-Hz.(Okamoto et al., 2004) This step is applied to remove any high-frequency noise that may be present in the data, such as line noise (mainly at 50 Hz) and other electrical interference from external sources. It also removes any low-frequency noise, such as drift, that could bias the results. Actually main frequency bands that we need, are below the 49-Hz.

2) Next, the channel information was set based on the 10-20 standard system which will be mapped into the MNI coordinate system. (Montreal Neurological Institute, n.d.) This step is important to ensure that the data is properly aligned and that the correct channels are being analyzed.

3) Then, line noise at 50 Hz was removed using the Clean-Line algorithm (8). This step is important because line noise can produce large artifacts in the data that can bias the results, However, by applying the band-pass filter from 1-Hz to 49 Hz, this problem has been reduced to some extent.

4) In the fourth step, the *clean_rawdata()* function was used to reject bad channels and correct continuous data using the Artifact Subspace Reconstruction(ASR) method (16).This step is important to remove any remaining artifacts or outliers in the data that could bias the results.

5) Following this, interpolation of all the removed channels was done. This step is important to ensure that the data remains continuous and that there are no missing data points.

6) The data was then re-referenced to the average. This step is important to ensure that the data is properly aligned and that the correct channels are being analyzed. Also, this step reduces the effect of noises that are commonly applied to all channels.

7) Independent component analysis (ICA) was then run using AMICA by the function tunica() with the 'PCA' option. (Palmer, J., Makeig, S., Kreutz-Delgado, K., & Rao, B. D. (2007). AMICA: a method for rapid, spatially independent component analysis of fMRI data. NeuroImage, 34(1), 217-235.) This step is important to separate the different sources of activity in the data and to identify any independent components that may be relevant to the research question.

8) Single equivalent current dipoles were estimated next. This step is important to estimate the location of the sources of activity in the brain that is responsible for the independent components identified in the previous step.

9) Then, symmetrically constrained bilateral dipoles were searched and estimated. This step is important to identify any sources of activity that may be correlated across the left and right hemispheres of the brain.

10) Probabilistic IC labels were then generated using *IClabel()* for IC rejection. This step is important to identify any independent components that may be artifacts rather than true sources of activity.

11) Finally, the IC-rejected data was epoched from -1 to 2 seconds relative to the event onset. This step is important to align the data with the relevant events and to make it more suitable for analysis. The labels identified in the previous step can be seen in the figure 15 below. In this step, components with muscle, eye blink, and line noise labels were removed.

At the group level, the data was processed using the STUDY. the design function of EEGLAB, which allows for statistical analysis of the data across multiple subjects (8). Overall, the Makoto pipeline is a robust method for pre-processing EEG data that helps to improve the quality of the data and make it more suitable for analysis. It includes a series of steps that are designed to remove artifacts and outliers, aligns the data, and identify relevant sources of activity in the brain.

tACS Stimulation. In the present study, transcranial alternate current stimulation (tACS) was used to investigate the effect of this stimulation on human bistable perception. During the experiment, participants were shown images of rotating cylinders and were asked to press the key when they recognized that the direction of rotation of the cylinder had changed (from right-handed to left-handed or from left-handed to right-handed). The tACS was applied over the back of the head, specifically over the Cz to Oz area, at a frequency of 40 Hz.

tACS is a non-invasive brain stimulation technique in which a weak direct current is applied to the scalp, with the goal of modulating brain activity. In this case, a 40 Hz frequency was chosen based on previous research indicating a relationship between this frequency and perception. The current was delivered using a battery-driven constant current stimulator, which was connected to two electrodes placed over the scalp. The size of the electrodes was 35 cm2, the current was applied at a strength of 1 mA and the stimulation duration was 20 minutes.

The tACS protocol was chosen to allow the investigation of the effect of stimulation on human bi-stable perception. The results of this study can contribute to a better understanding of the relationship between brain activity and perception, and may have implications for the development of new methods for the treatment of perception-related disorders.

Time Analysis. To plot the amount of electroencephalogram (EEG) signal in a raster form, we will choose a threshold for the signal and if the amount was more than the chosen threshold, we would plot the point (figure 16-20). The result of raster plots for each channel shows that for channels number 22, 23 and 24 (Pz, CPz and Oz) the EEG signal has more magnitude and we can conclude that these areas are active more than other parts.

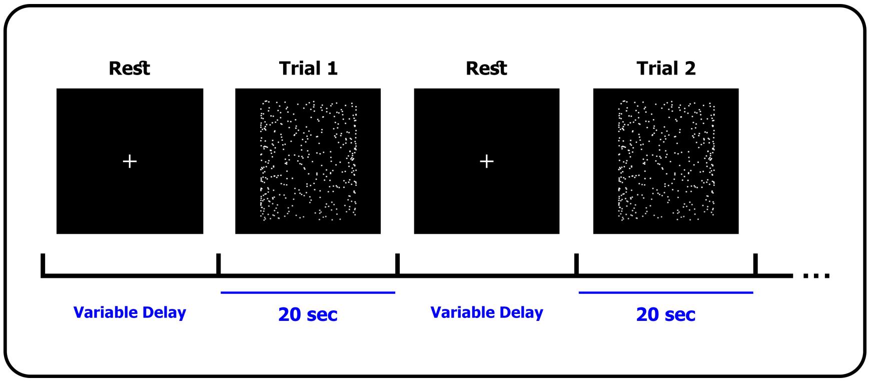

Fig. 14. Perception Task; At first a black screen appears and the subject presses *Enter button* when ready. Trial 1 starts for a period of 20 seconds. Meanwhile, the subject informs their decision to switch in rotating by means of pressing *right button* (for counter-clockwise) or *left button* (for clockwise). Again black screen appears and the subject is free to have a few seconds to rest. By pressing the *Enter button* again, the next trial begins.

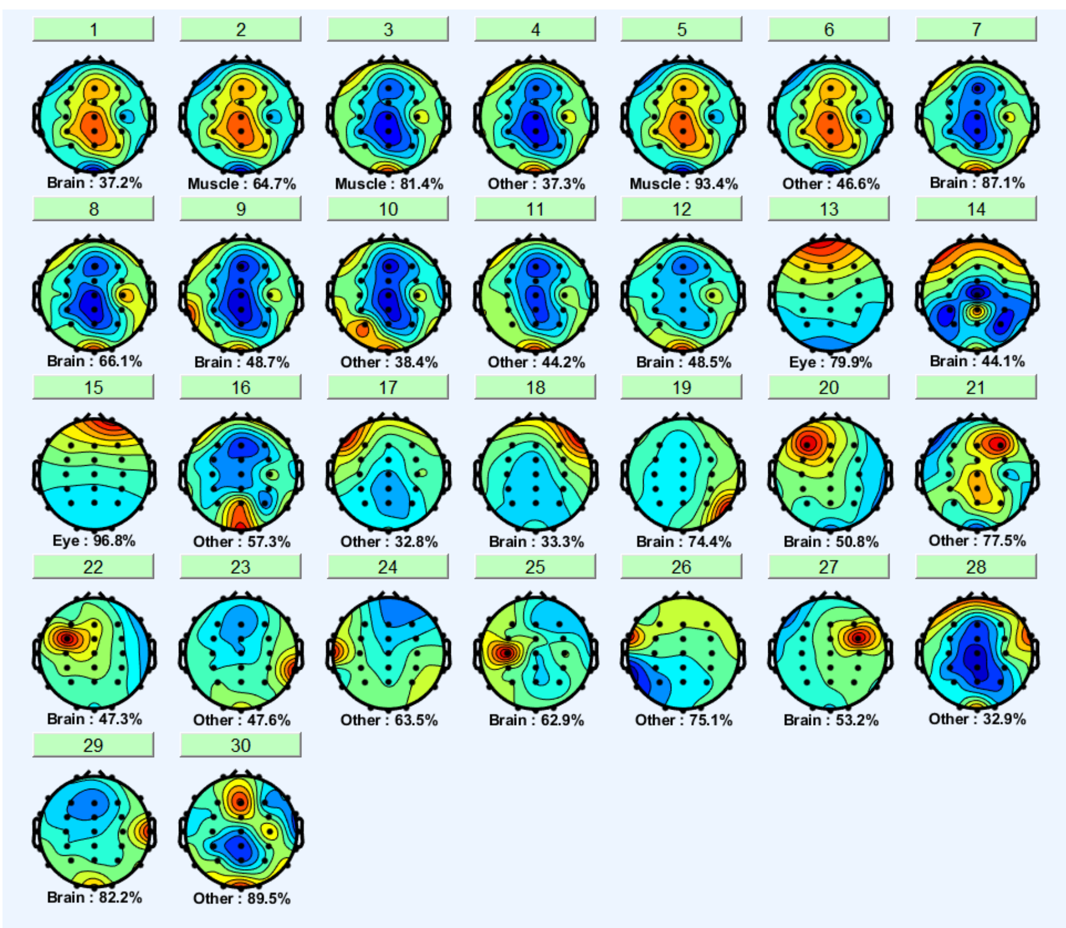

Fig. 15. IClabeled components recorded signal.

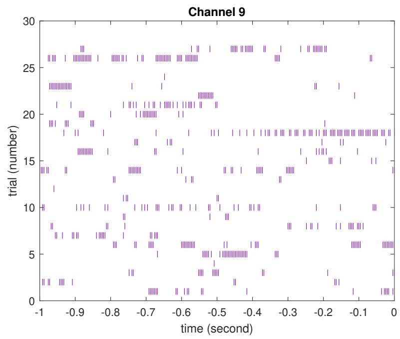

Fig. 16. Raster Plot of epochs in channel O2, 1 second before response

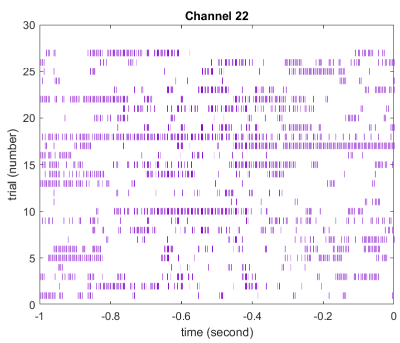

Fig. 17. Raster Plot of epochs in channel Pz, 1 second before response

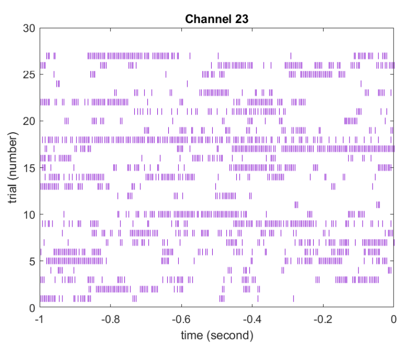

Fig. 18. Raster Plot of epochs in channel CPz, 1 second before response

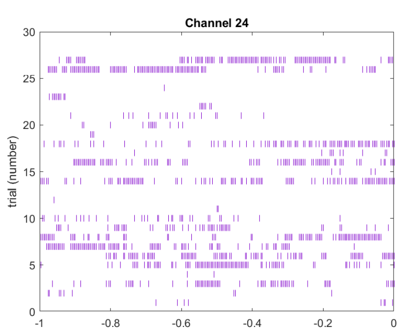

Fig. 19. Raster Plot of epochs in channel Oz, 1 second before response

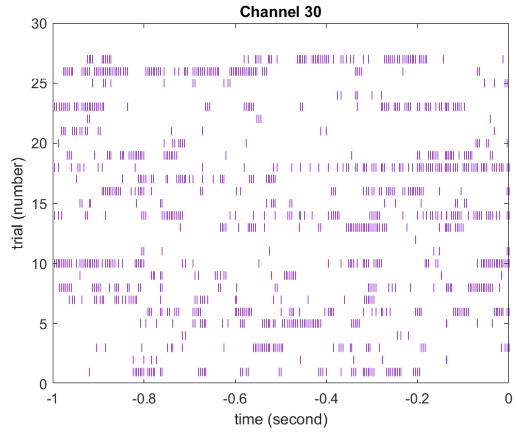

Fig. 20. Raster Plot of epochs in channel F7, 1 second before response

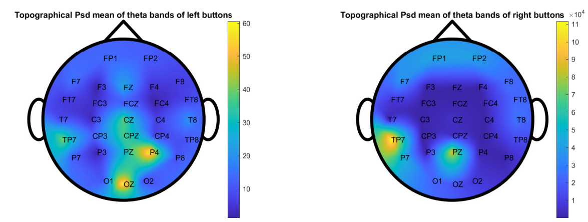

Fig. 21. Mean Power Spectral Density of left/right responses in θ band

Frequency Analysis. To plot the power spectral density (PSD) of each channel in an electroencephalogram (EEG) signal in a topographical format, we will calculate the PSD for each channel using a Fast Fourier Transform (FFT) and then map the results on a graph. The graph will show the power spectral density per each frequency band (Alpha, Beta, Gamma, theta) for each channel in a topographic layout, which will allow us to visualize the power distribution of different frequency bands across the channels in the EEG signal (figure 21-24).

Time-Frequency Analysis. The goal of time-frequency analysis is to understand how the spectral frequency change with time, for example, when we have a stimulus and want to show how frequency properties change after that stimulus. Short-time Fourier transform (STFT) is one of the time-frequency tools. At first, the signal is multiplied by a window function that is nonzero in a short period (usually by Gaussian or Hamming window). The Fourier transform of the resulting signal is derived and the window slips along the signal. We use Short-time Fourier transform and plot the squared magnitude of

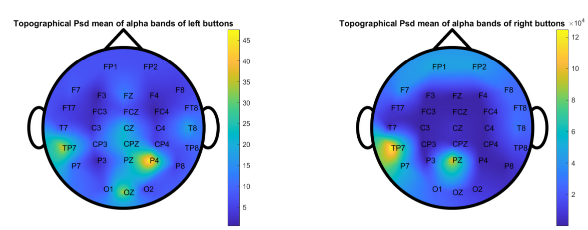

Fig. 22. Mean Power Spectral Density of left/right responses in α band

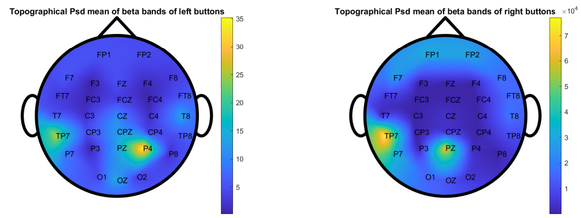

Fig. 23. Mean Power Spectral Density of left/right responses in β band

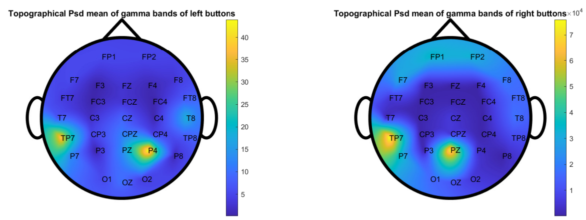

Fig. 24. Mean Power Spectral Density of left/right responses in γ band

the STFT as a spectrogram. It represents the power spectral density of the signal over time.

$$STFT\,\{x(t)\}\,(\tau, w) = X(\tau, w) = \int_{-\infty}^{\infty} x(t)w(t-\tau)\exp^{-wt}dt$$

EEG phase synchrony analysis. Phase lock value is used as functional connectivity to measure the degree of synchronization in EEG signal. The data were filtered into 5 frequency bands using a band-pass filter: 1-4 Hz (Delta), 4-8 Hz (Theta), 8-13 Hz (Alpha), 13-30 Hz(Beta), and 30-100 Hz (Gamma). In each band, we perform the PLV as follows:

The amplitude $A(t)$ and the instantaneous phase $\phi(t)$ of a signal $s(t)$ can be estimated using the Hilbert transform $H\{.\}$:

$$z(t) = s(t) + i.H\{s(t)\} = A(t).\exp^{i\phi(t)}$$

The analytic signal $z(t)$ can be taken as an embedding of the one dimensional time series in the two dimensional complex plane. The phase is computed by the following expression:

$$\phi(t) = \arctan(\frac{Im\{z(t)\}}{Re\{z(t)\}}) = \arctan(\frac{H\{s(t)\}}{s(t)}) \qquad \phi \in [-\pi, \pi]$$

The phase synchronization is defined as the locking of phases of two oscillators:

$$\phi_{12}(t) = \phi_1(t) - \phi_2(t) = const$$

where $\phi_1(t)$ and $\phi_1(t)$ denote the phases of the oscillators, and $\phi_{12}(t)$ is defined as their relative phase. The phase-locking value (PLV) is defined as:

$$PLV = \left| \frac{1}{N} \sum_{j=0}^{N-1} \exp^{j\phi_{12}(j\Delta t)} \right|$$

where i–imaginary unit; N–the total number of samples; ϕ_{12}–the relative phase of two signals; Δt–time between the successive samples j from 1 to $N-1$ (17) The value of PLV is bounded between zero and one with zero value indicating unsynchronized phases and one value indicating when the phase difference is constant, i.e. the synchronization of signals is perfect. A decrease of the phase-locking value between two signals indicates a loss of synchronization between them.

Graph Theory. In graph theory, the brain is modeled as a graph in which nodes represent the specific brain region or EEG channels, and edges represent the connectivity between each node (functional connectivity or effective connectivity). Various graph indices allow us to analyze the brain as a network, show the efficiency of information transfer in this network, and the balance between segregation and integration.

System segregation means the separation of communication in the brain network or the ability for specialized processing within densely interconnected groups of nodes (clusters or modules). If the nearest neighbors of a node are also directly connected to each other, they form a cluster. The clustering coefficient quantifies the number of connections that exist between the nearest neighbours of a node as a proportion of the maximum number of possible connections. Random networks have low average clustering, whereas complex networks have high clustering (associated with high local efficiency of information transfer and robustness). Interactions between neighboring nodes can also be quantified by counting the occurrence of small motifs of interconnected nodes. The distribution of different motif classes in a network provides information about the types of local interactions that the network can support (18).

System Integration means the efficiency of global information communication or the ability to combine distributed information. Specifically, the global efficiency is inversely related to the topological distance between nodes and is typically interpreted as a measure of the capacity for parallel information transfer and integrated processing.

Also, some nodes are critical for communication between different brain regions. Centrality is a criterion that accounts for the importance of a node in facilitating interactions between other nodes in a network. It is defined as the ratio between the number of shortest paths (defined as the smallest number of edges between two nodes) passing through a specific node and the total number of shortest paths in the network. At first, we calculate the phase lock value between pair of channels as functional connectivity. Then the median of all PLV is used as a threshold to construct a binary graph. We calculate the global efficiency as an integration index, the clustering of each node as a segregation index, and the betweenness and closeness centrality for each node (19).

Clustering:

$$c_i = \frac{2t_i}{k_i(k_i-1)}$$

$$t_i = \frac{1}{2}\sigma_{i\to j\to k}a_{ij}a_{ih}a_{jh}$$

$$k_i = \sum_{i \neq j} a_{ij}$$

$$C = \frac{1}{N}\sum_{i=1}^{N} c_i$$

Global Efficiency:

$$E_{global} = \frac{1}{N(N-1)}\sum_{i \neq j}\frac{1}{d_{i,j}}$$

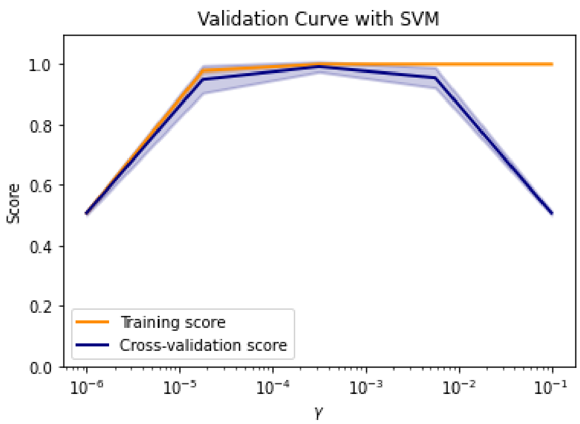

Fig. 25. SVM validation curve

Closeness Centrality:

$$C_b(i) = \frac{N-1}{\sum_{i \neq j} l_{ij}}$$

Betweenness Centrality:

$$C_b(i) = \frac{2}{(N-1)(N-2)} \sum_{i \neq j \neq h} \frac{n_{hj}(i)}{n_{hj}}$$

where;

$n_{hj}(i)$ is the number of shortest paths from h to j that pass through node i, and n_{hj} is the total number of shortest paths from h to j.

Classification. According to the results of the previous steps, it was tried to implement a classifier with two different methods based on SVM and based on a combined model of CNN and LSTM, and also measure their performance. In fact, the purpose of classification between the recorded EEG signal was in two different states during perceptual switching.

Data preprocessing: Before training the model, we considered the epoched EEG signal, which is divided into two categories based on the detection of the perceptual switch from right to left or left to right. We considered the signal for the interval of one second before the response time. This data included 30 channels, 250 samples (equal to the sampling rate) per epoch, and 1178 responses. After shuffling and mixing the order of data randomly, 20% of this data was used as test data and 80% was used for training the model.

SVM-based Classification model: To prepare the classifier, based on the results obtained from the frequency and time analysis stages, from various features including the average frequencies in different frequency bands (delta, theta, alpha, beta, gamma), the peak frequency in each of these spectrums. The time signal itself was tested in different channels and in all tests, the classification performance (accuracy criterion) was in the range of 49% to 52%, which as a binary classification problem practically means random and meaningless performance.

Mixed LSTM and CNN-based model: In the next step, a trainable model was provided with a combination of a CNN decoder and a network of LSTM blocks. The 1-D convolutional layer acts as a decoder with the output dimension of 246 = ((100020)/4+1). A total of 40 features are extracted by the CNN layer, which are high-level temporal features of the original sequence. Then, the LSTM layers can perform classification on these high-level features.

	precision	recall	f1-score	support
0	0.71	0.87	0.78	116
1	0.84	0.65	0.73	120
accuracy			0.76	236
macro avg	0.77	0.76	0.76	236
weighted avg	0.77	0.76	0.76	236

Table 1. Performance evaluation results of the mixed model

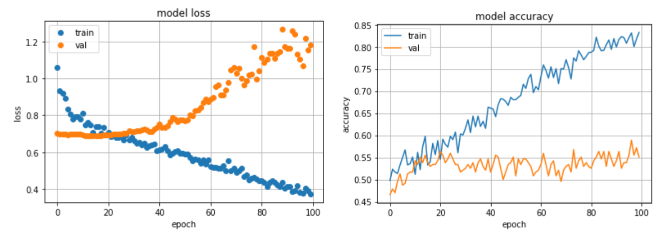

Fig. 26. Mixed model properties

This model was implemented using the TensorFlow (20) library in Python. Before the training, the recorded data shuffled with a random seed to forbid the influence of data recording order. And also mean-subtraction on axis=1 (time sequence dimension). Optimizer: Adam Loss function: CrossEntropyLoss was set before fitting the model on the data. You can see the summary of the architecture of the combined model and the distribution of parameters in figure 2.

t-Test. In this section, we will calculate the time between both successive responses for two states with tACS stimulus and without stimulus. A distribution is obtained from the histogram of a non-stimulus task, then we calculate the average times between two responses for stimulus one and run a t-test on it.

Our null hypothesis is that mean of the two histograms does not differ.

Student's t-Test Result: The value obtained from the student's t-test, taking into account that the two observed distributions do not necessarily have the same variance, the value of 2.20339246e-19 for the p-value and -9.72365427 for The calculated t-statistic was obtained, which well confirms the proposed hypothesis.

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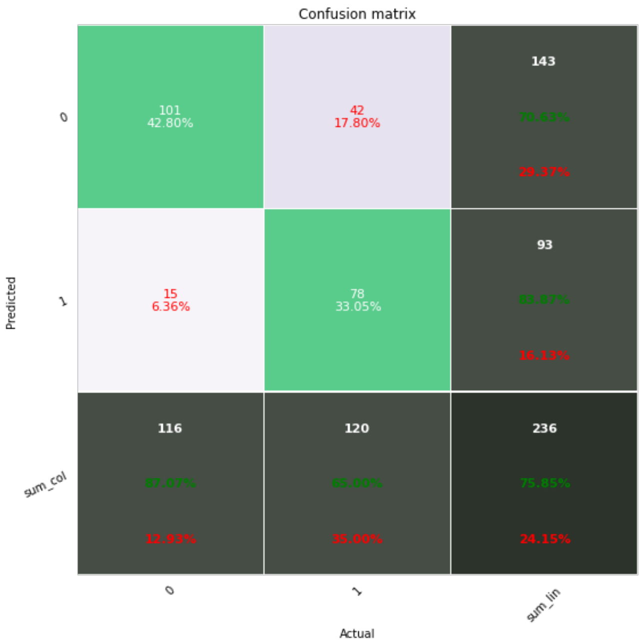

Fig. 27. Confusion matrix for mixed model

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Layer (type)	Output Shape	Param #
conv1d_3 (Conv1D)	(None, 58, 40)	24040
activation_3 (Activation)	(None, 58, 40)	0
dropout_16 (Dropout)	(None, 58, 40)	0
batch_normalization_11 (BatchNormalization)	(None, 58, 40)	160
max_pooling1d_3 (MaxPooling1D)	(None, 14, 40)	0
lstm_18 (LSTM)	(None, 14, 30)	8520
dropout_17 (Dropout)	(None, 14, 30)	0
batch_normalization_12 (BatchNormalization)	(None, 14, 30)	120
lstm_19 (LSTM)	(None, 14, 20)	4080
dropout_18 (Dropout)	(None, 14, 20)	0
batch_normalization_13 (BatchNormalization)	(None, 14, 20)	80
flatten_3 (Flatten)	(None, 280)	0
dense_14 (Dense)	(None, 2)	562

Total params: 37,562
Trainable params: 37,382
Non-trainable params: 180

Table 2. Summary of mixed model architecture and number of trainable parameters

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