Project report - NeuroBeatsDL

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Title:

Deep learning Analysis of EEG patterns to evaluate the impact of binaural beats on attention span.

Abstract:

This project integrates deep learning with image processing and computer vision techniques to quantify the impact of binaural beats on attention span by harnessing EEG data collected across 42 electrodes on the human scalp (from an ongoing UB study). The methodology extends beyond the traditional signal analysis by preprocessing the EEG signals into brain heat maps – topographical representations of brain activity – leveraged as input into neural network architectures like conditional Generative Adversarial Networks (GANs), 3D Convolutional Neural networks, autoencoder transformer models and diffusion models. The networks are designed to anticipate how the brain heat map would evolve in the ensuing moment, hence providing a dynamic measure of attention span, indicated by the color-coded contour lines of the active brain regions. By comparing these predictions in the presence and absence of binaural audio, the project performs a nuanced exploration of how auditory stimuli modulate human neural activity, highlighting the potential of combining deep learning with image processing to understand attention mechanisms.

Problem statement

To determine the extent to which binaural beats affect human attention span by analyzing EEG data with neural network architectures. Specifically, this project deals with raw EEG signals recorded from the human scalp across 42 channels, preprocessing them into GAN neural nets, and predict the subsequent state of these maps. The primary challenge is to develop a model that can accurately interpret the complex patterns in EEG derived images to dynamically gauge attention span, as visualized across contour lines in the active regions of the brain. By comparing the model outputs with and without exposure to binaural audio, the project seeks to find underlying relationships between auditory stimuli and brain neural activity patterns.

Background

This deep learning project inherits the EEG data from a recently completed undergraduate study, ***Binaural Beats for Focus: Exploring Binaural Beats Parameters for Enhancing Sustained Attention*** conducted by the Department of Psychology, University of Buffalo. The provided EEG data has been deidentified to protect the confidentiality of the participants involved. This study, which is still under works for publication, conducted 33-minute cognitive ability sessions in the presence and absence of binaural beats for each participant and recorded their EEG signals via 42 electrodes. The sessions were followed by self-reported questionnaires for the participants, which led them to the conclusion that binaural beats enhance attention span.

This deep learning project aims to employ neural networks to study the brain heat maps of these recorded EEG signals, and predict a brain heat map of the individual at the next time stamp, hence providing visual analysis of their attention span based on their active brain regions.

Dataset:

The dataset involves raw EEG signal files recorded in BIO SEMI Active Two Brain recorder, and exported in (.BDF) format. The data consists of deidentified data for 80 participants, recorded for 2 sessions of 30 minutes durations, out of which one session had just pure tone, while the other session had binaural beats. The EEG signals have a sampling frequency of 512 Hz. Each session consisted of 33 minutes, where the participant had to answer 1200 cognitive ability questions, and their brain activity was recorded via EEG, and their wrong answers were counted. These 1200 questions had a stimulus window of 1500 ms and a response window of 150 ms, hence the total duration of the question was 1.65 seconds.

1. Brain rate is calculated for each epoch by weighting the centroids of the frequency bands by their relative power contributions. The formula used effectively integrates information across the frequency spectrum to provide a singular measure of brain activity.
2. Normalization of brain rates by subtraction of baseline brain rate: The cognitive session brain rate values are normalized using the baseline brain rate value computed during the relaxation phase of the session. This is done to correct any inherent biases or non-task related activity.

The sparse nature of incorrect answers in the dataset led to the calculation and employment of brain rate as a continuous metric rather than binary labels, allowing for a more nuanced analysis of the EEG data. This methodology provides a robust framework for understanding and quantifying EEG data in research or clinical settings where standard metrics or labels prove to be inadequate for capturing the complexities of brain activity.

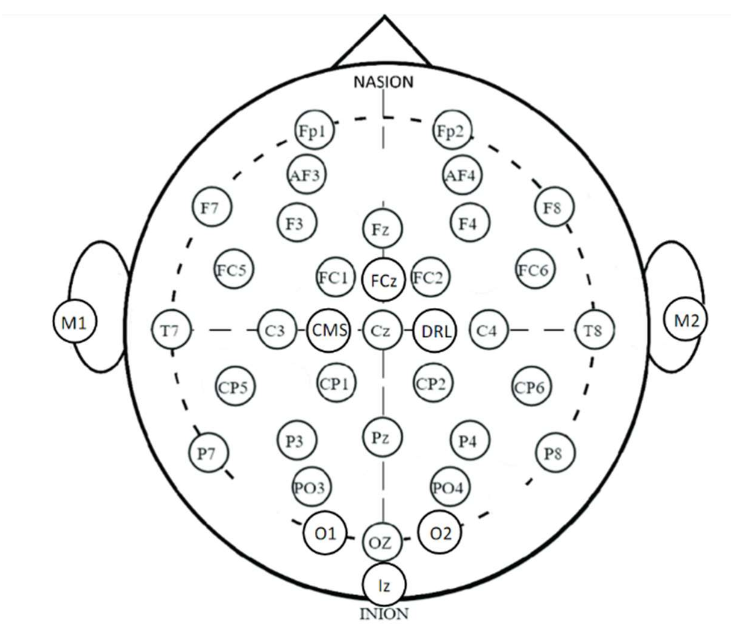
Vital information about the signals

These functions of these electrodes are explained in the below table, along with the positioning of these electrodes on the human brain following the international standard 10-20 system.

Electrode	**Description**	**Targeted Brain Area**
Fp1, Fp2	Frontopolar	Frontal lobe, near the forehead, dealing with executive functions and voluntary movement
AF3, AF4	Anterior Frontal	Frontal lobe, responsible for high level cognitive functions
F7, F8	Frontal	Lateral frontal areas dealing with motor function and language
F3, F4	Frontal	Central frontal areas dealing with decision making and problem solving
FC1, FC2, FC5, FC6	Frontocentral	Bridge between frontal and central areas, associated with motor control
T7, T8	Temporal	Middle temporal areas responsible for memory and hearing

C3, C4	Central	Central brain associated with sensorimotor coordination
CP1, CP2, CP5, CP6	Centroparietal	Linking central and parietal lobes, vital for sensory integration
P7, P8	Parietal	Lateral parietal areas involved with orientation and perception
P3, P4	Parietal	Central parietal areas crucial for sensory input and spatial orientation
Pz	Parietal midline	Top of the head responsible for somatosensory processing
PO3, PO4	Parietal Occipital	Near the visual cortex, important for visual processing
O1, O2	Occipital	Back of the head, primary visual processing area
Oz	Occipital midline	Central occipital, key in visual data processing
VEO+, VEO-	Vertical EOG	Vertical eye movement
HEOL, HEOR	Horizontal EOG	Horizontal eye movement
FCz, Cz	Central midline	Central area of the head involved for motor function
Iz	Inion	Near the back of the skull, used for referencing the EEG
M1, M2	Mastoid reference	Located near the mastoids behind the ears (left and right earlobes), used for referencing the EEG signals
B9, B10	Additional	Supplementary electrodes for specific studies

The above-mentioned electrodes are placed all across the human brain, in the following layout:



Milestone 1: EEG Preprocessing

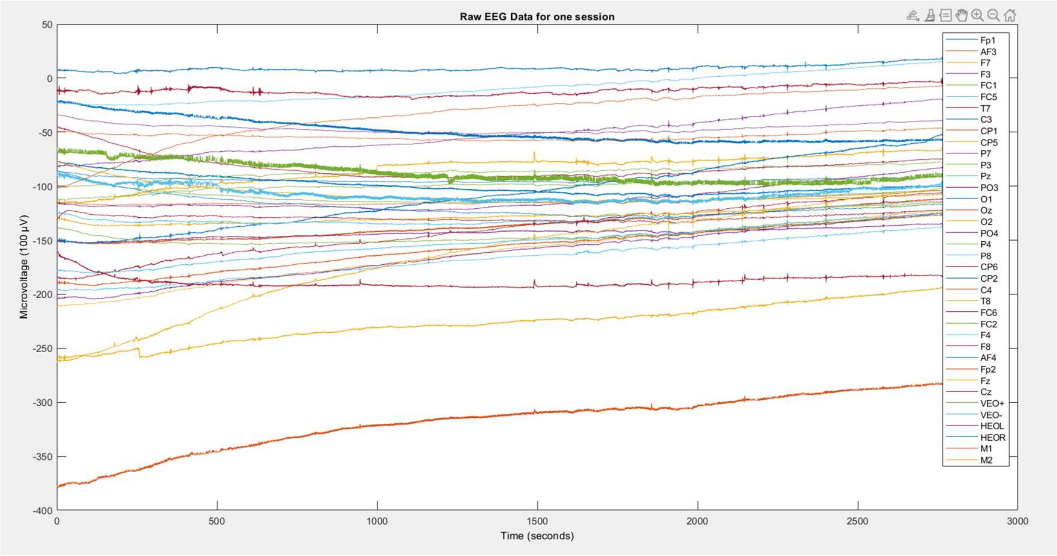
Methodology

Signal preprocessing - (Preprocessing pipeline.m)

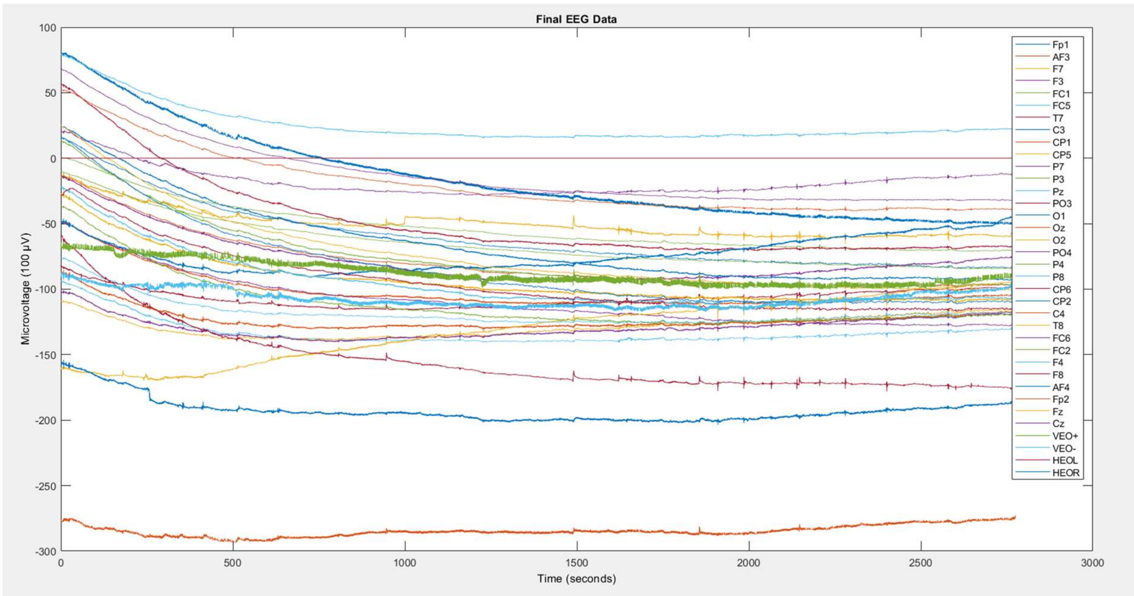
Software: MATLAB (EEGLAB toolbox)

1. The raw EEG dataset for a single user, for a single session is imported into the EEGLAB on MATLAB.
2. Two marker files: **Artifact rejection and ocular correction** are also imported for that user. These files are obtained after visualizing the signals on an external software, called Brain Vision Analyzer, which is capable of recognizing the noise in the data due to muscle movements, eye blinks, nose twitches etc.
3. Before applying the marker information for artifact rejection, we visualize the raw EEG data to make sure that the signals are static and ready for preprocessing.
4. However, on visualizing the EEG signals, on a single plot, a trend is observed in the data. This means that the brain signals aren't as static as required for the analysis. Hence, we decide to re-reference the EEG signals, based on the mastoids (M1 and M2) signals, which are referred to as ground signals, and correspond to the left and right earlobe respectively.
5. During re-referencing, it is important to exclude non-brain activity signals from the analysis. Hence, certain EEG channels like VEO+. VEO-, HEOR, HEOL, B9 and B10 are excluded from the data, during re-referencing, but not dropped due to their utility during ICA decomposition.
6. The re-referenced signal shows a much better static trend and then gets pre-processed by applying the marker information of artifact rejection and ocular correction.
7. This final signal is then decomposed using Independent Component Analysis, in order to clean out any extra noise.
8. The data contained in the final clean signal is written into a .csv file, as channel data matrix and time vector.

Visualization of the raw EEG signal:



Visualization of the preprocessed EEG signal:

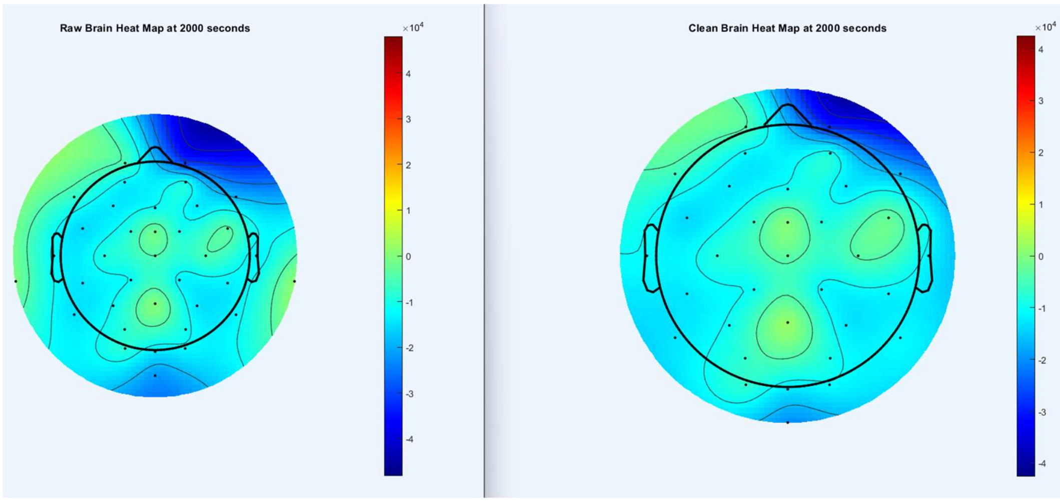


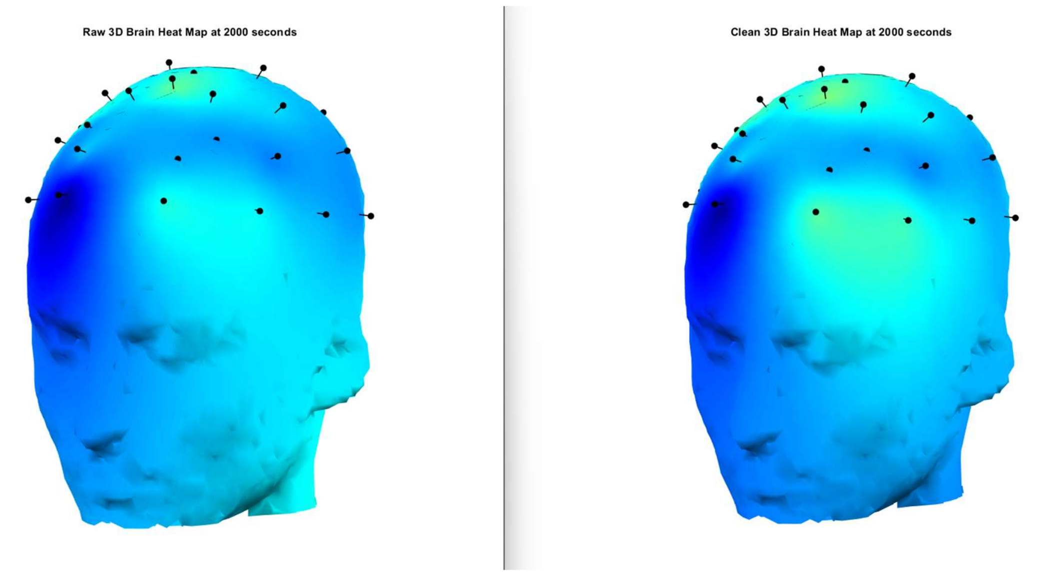
Observations to be noted:

1. Baseline correction: The raw EEG signal has baseline drifts moving upwards with time. These have been corrected in the pre-processed signal by re-referencing the channel signals.
2. Artifact removal: Noise due to artifacts such as eye blink (VEOG), cardiac signals, muscle contractions have been filtered out in the second image as evident by the absence of sharp spikes, resulting in a much more stable pattern of brain activity.
3. Normalized amplitude fluctuations: Amplitudes are normalized to a certain range to avoid variations due to electrode impedance, in the second signal.

The signal to noise ratio has been increased to approximately 17%. This difference in the two signals is further amplified on illustrating the topographical map of the brain for raw and pre-processed data.

The brain heat map (or topographical map) for a single sample at 2000s is compared between the raw and cleaned EEG signals.





The above plots can be displayed using the D2_plot and D3_plot script (given in zip folder).

Observations to be noted:

1. The raw signal in the 3D brain heat map contains more areas of intense color indicating a greater range of signal values. This is because of the presence of noise and artifacts, which have not been filtered out yet.
2. The clean signal in the 3D brain heat map appears smoother with lesser variation in the color intensity across the scalp. This clearly illustrates that the signal has been cleaned to reflect only the brain activity (while ignoring all other signals) accurately.
3. The raw signal in the 2D brain heat map shows distinct peaks and troughs, depicting areas of high and low electrical activity. The presence of these sharp contours illustrate noise, artifacts, which cause abrupt spikes in the voltage.
4. The clean signal in the 2D brain heat map shows a smoother distribution of electrical activity. The contours are much more gradual and peaks are less pronounced.

Milestone 2: Data Feature extraction

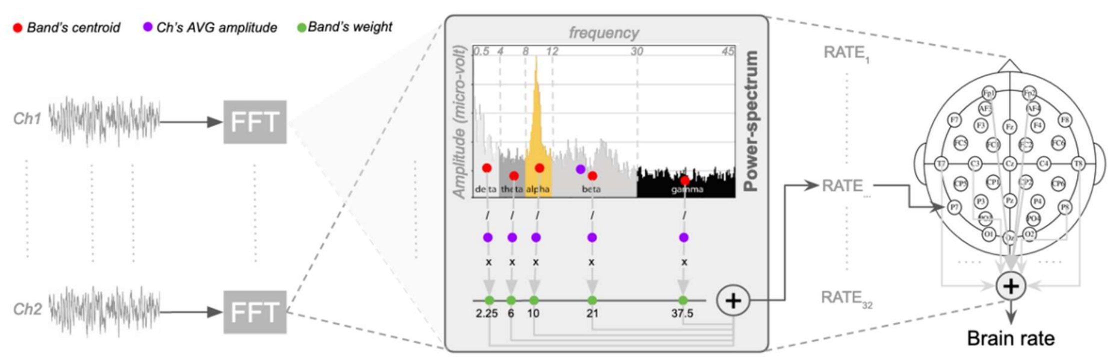
Problem with existing label of the dataset:

The dataset's cognitive ability questions proved to be an imbalanced label for the EEG processed brain maps. This was because each participant would get on average, only 10 to 20 questions wrong out of 1200 and these wrong answers are scattered throughout the dataset.

As a result, the CNN and CNN+LSTM model was unable to learn from the dataset based on the number of correct answered questions as the label. The correct answers were labelled as 1 and wrong answers were labelled as 0. Due to the sparsity of wrong answers, the model is unable to generalize its learning.

Defining a novel metric (brain rate) as the label:

There was a need to define a **single scalar quantity** that would describe the EEG data (across 42 channels) for each timestep of the session. Taking inspiration from a novel metric defined in a research paper, we developed a brain rate variable that would be used to describe the data.



The above figure illustrates the steps required to calculate the brain rate for an EEG signal of a user.

Before we jump into the methodology of how the brain rate variable is calculated, it is necessary to understand the different frequency bands present in EEG signals, and how they influence the cognitive processes. This literature was essential in determining the weights given to each frequency band while calculating the scalar value of the brain rate.

Cognitive EEG frequency bands

The electroencephalogram (EEG) signals are divided into different frequency bands, each associated with different types of brain activity, including cognitive processes. The most important frequency bands for finding cognitive brain activity are:

1. Delta Waves (0.5 to 4 Hz):
   Although primarily associated with deep sleep, delta waves can also be related to certain cognitive processes in some pathological states.
2. Theta Waves (4 to 8 Hz):

Theta waves are often linked to memory, learning, and navigation. They are particularly prominent during meditative, drowsy, or sleeping states but also appear during deep emotional experiences and cognitive activities that require concentration and focus.

3. Alpha Waves (8 to 12 Hz):
   Alpha waves are associated with a state of relaxed alertness and rest. They become prominent when a person is calm and physically and mentally relaxed but still alert. Alpha activity is often related to the brain's idle state or resting state and has been linked to creativity and the reduction of depression.
4. Beta Waves (12 to 30 Hz):
   Beta waves are associated with active, analytical thought and alertness. This frequency band is most commonly observed during active conversation, problem-solving, decision-making, and focused mental activity. High levels of beta activity are associated with stress, anxiety, or excitement.
5. Gamma Waves (30 Hz and above):
   Gamma waves are associated with higher mental activity, including perception, problem-solving, fear, and consciousness. High-frequency gamma activity is linked to the processing of information from different brain areas simultaneously, essentially integrating thoughts and experiences.

Each of these frequency bands plays a role in different aspects of cognitive processing and brain activity. For cognitive tasks and states of consciousness, alpha, beta, and gamma waves are particularly significant, as they are directly related to how we think, learn, and process information. However, the importance of a specific band can vary depending on the type of cognitive activity being performed.

Fast Fourier transforms & Power spectral density

Fast Fourier transforms is a vital mathematical tool used in analysing EEG data that transforms time-domain signals into frequency domain. This transformation is crucial because it:

- Enables spectral analysis of human brain’s electrical activity in terms of frequency components.
- Efficiently computes the Discrete Fourier Transform (DFT) of a sequence which contributes significantly to handling large volumes of EEG data for quick effective analysis.
- Provides insight into patterns that aren’t visible in the time domain, for example the brain states associated with alertness are associated with certain frequency bands (alpha waves for relaxation, beta waves for alertness).

Power Spectral Density (PSD) is a function that describes the power distribution of a signal across various frequencies. It is computed from FFT results to quantify the power present at each frequency component of the EEG signal. PSD is necessary as it:

- Provides a quantitative measure of signal power across frequencies which is essential to assess brain activity linked to different neurological conditions.
- Offers a more condensed, low dimensional representation of the EEG data hence reducing data complexity while retaining critical information about the signal’s power distribution making it more manageable and interpretable.

Formula for Brain rate calculation:

Brain rate is defined as a sum of the mean frequencies of brain oscillations weighted over the EEG bands (delta, theta, alpha, beta, and gamma) of the power spectrum for each channel.

$$BR = \sum_{ch=1}^{n} \sum_{b=1}^{5} f_b \, . \, P(b, ch)$$

- b is the index of the frequency bands (1 for delta, 2 for theta, 3 for alpha, 4 for beta, 5 for gamma),
- f_b is the weight associated with each frequency band b. This is the mean frequency of that band (given in Hz).
- $P(b, ch)$ is mean amplitude of the electrical potential for band b of each channel ch over the mean of all its amplitudes.

In simple terms, $P(b, ch)$ is the power ratio of a specific EEG frequency band over a channel.

$$P(b, ch) = \frac{avg_b(FFT_{ch})}{avg(FFT_{ch})}$$

- $P(b, ch)$ is the power ratio for frequency band b and channel ch.
- FFT_{ch} is the vector containing the amplitudes of the FFT transformed channel.
- $avg_b(FFT_{ch})$ is the average (centroid) of the amplitudes within the frequency band b from the FFT-transformed channel ch. It is the centroid of the band's amplitudes within that frequency range.
- $avg(FFT_{ch})$ is the average of all amplitudes across the entire spectrum from the FFT-transformed channel ch.

$P(b, ch)$ shows the contribution of the band b to the channel's overall signal. The higher the ratio, the more dominant that particular frequency band is in the channel's signal.

Methodology for brain rate calculation

3. Pre-processed EEG datasets (after applying artifact rejection and ocular correction) are loaded into MATLAB's EEGLAB tool.
4. The EEG data is resampled from 512 Hz to 128 Hz, to reduce the number of samples (brain maps) generated per second, while retaining all crucial information. If we sample to 64 Hz, the Nyquist frequency would be 32 Hz (half of sampling frequency), leading to loss of gamma frequency band data.
5. The Fast Fourier transform is calculated for each channel of the EEG data.
6. The five distinct frequency bands are isolated using bandpass filtering. This separation of the data is essential for analysing specific ranges of brain activity related to different states.
7. Power spectral density of EEG data is calculated for each one-second epoch within the filtered frequency bands, hence quantifying the power present at different frequencies.
8. Centroids for each frequency band are computed which serve as baseline weights, helpful in capturing the dominant frequency within the band during each epoch.

9. Brain rate is calculated for each epoch by weighting the centroids of the frequency bands by their relative power contributions. The formula used effectively integrates information across the frequency spectrum to provide a singular measure of brain activity.
10. Normalization of brain rates by subtraction of baseline brain rate: The cognitive session brain rate values are normalized using the baseline brain rate value computed during the relaxation phase of the session. This is done to correct any inherent biases or non-task related activity.

The sparse nature of incorrect answers in the dataset led to the calculation and employment of brain rate as a continuous metric rather than binary labels, allowing for a more nuanced analysis of the EEG data. This methodology provides a robust framework for understanding and quantifying EEG data in research or clinical settings where standard metrics or labels prove to be inadequate for capturing the complexities of brain activity.

Milestone 3 – Image reconstruction

Model 1: CNN+LSTM2D

Function of model: Predict the frames for next second

This model architecture is built to perform next frame prediction of brain topographical maps, and uses a sequence of ConvLSTM2D layers followed by a Conv3D layer.

Layer	Operation
Input layer	Initializes the input to the model; accommodates an unspecified number of frames, and the shape of each individual frame. This flexibility enables the model to process variable length sequence of frames.
ConvLSTM2D layers	The model uses 3 such layers which are suited for sequence prediction problems (involving images, video frames). These layers processes the input data both in space and time, making them ideal for learning features from a sequence of frames.
a. First layer (kernel = 5x5)	Captures complex spatial relationships within the data. It outputs sequences of same temporal length as input.
b. Second layer (kernel = 3x3)	Continues processing, refining the features extracted by first layer.
c. Third layer (kernel = 1x1)	Adjusts the depth of feature maps before passing them to the Conv3D layer without altering spatial dimensions.
Batch normalization	Applied after each ConvLSTM2D layer to normalize the activations and speed up training by reducing internal covariate shift.

Conv3D	The layer aggregates the temporal information across the frames to make a final prediction. It outputs the predicted next frame (s) with the same spatial dimensions as the input frames, using three filters to match the desired output channels.
Model compilation	Done with Adam optimizer with Mean Squared Error (MSE) loss function. This is a common choice when predicting the next pixel values of the next frame.
Callbacks: Model checkpoint, Early stopping, ReduceLROnPlateau	Model checkpoint saves the model weights to a checkpoint file after each epoch if there is improvement in validation loss. Early Stopping stops training if the validation loss does not improve for five consecutive epochs. ReduceLROnPlateau reduces the learning rate if the validation loss doesn't improve for three epochs, which helps the model converge more effectively at later stages in training.

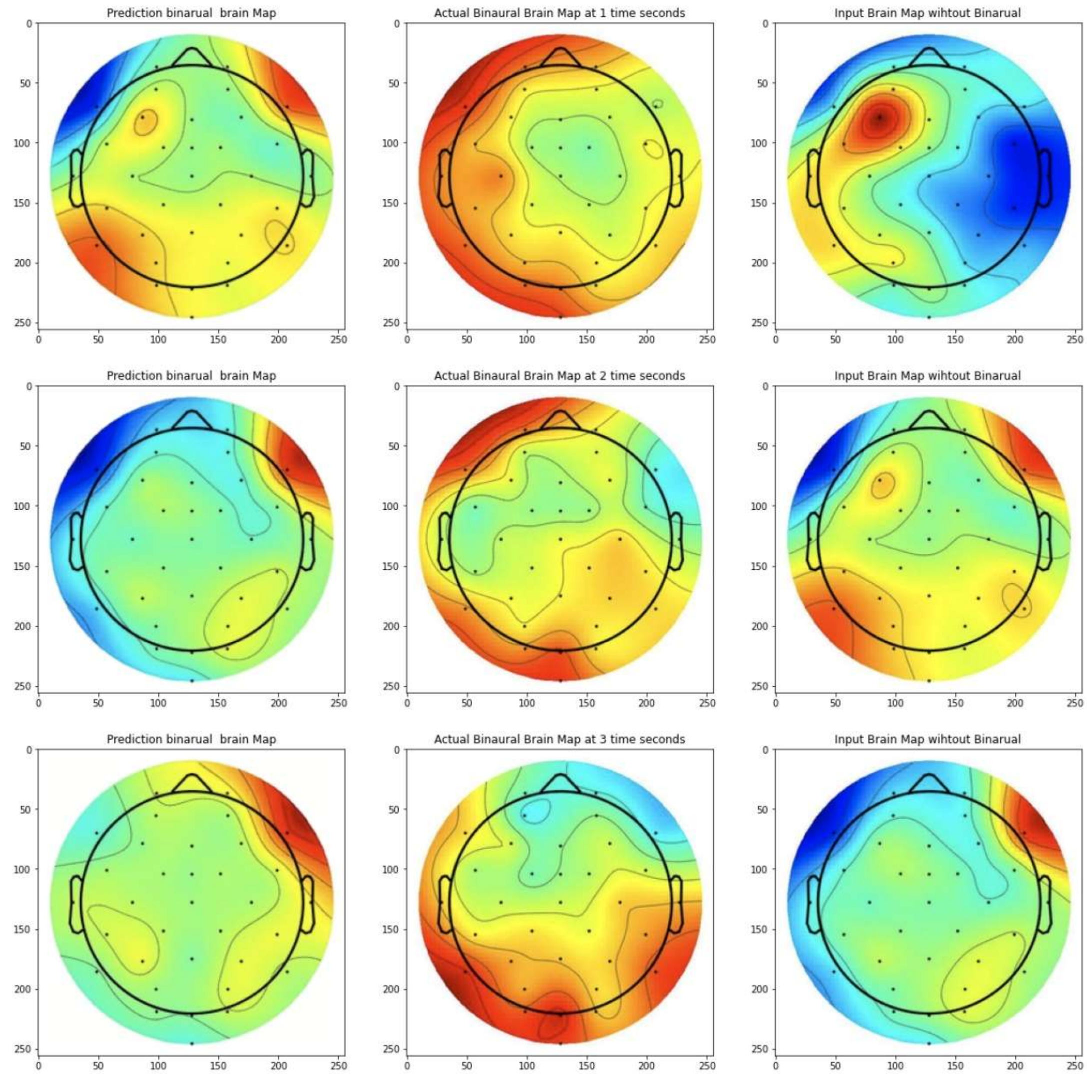
Training

The model was trained on 500 seconds of images consisting of normal and binaural brain topographical maps, where each second consists of 8 frames. This means that the 512 samples generated per second (since EEG sampling rate is 512) was down-sampled to 128 Hz and then averaged across 16 samples to generate 8 samples per second.

Testing

The model is then tested on a normal session input image to see if it can predict the binaural session image of the brain topographical map for that second. We repeat this for the next 7 frames of that second to see if the model can consistently produce the binaural session of that brain image or whether it fails.

This is our novel way of testing the learning capability of the model.



Observations:

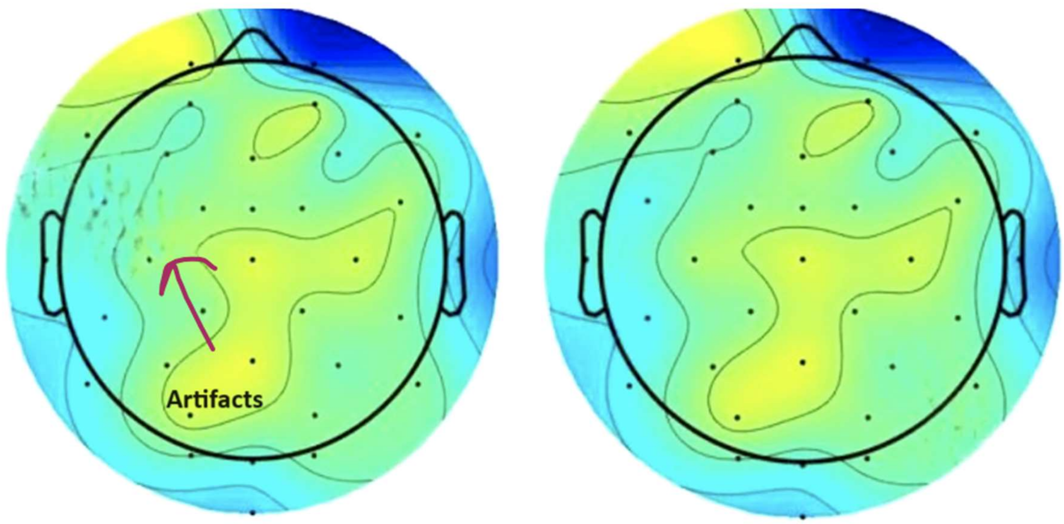
1. Consistency across time: The model consistently captures the general structure and spatial distribution of activity across the human brain, which is evident from the similarity in contours and color distribution between the predicted and actual maps. However, there is some noticeable difference which indicates that certain areas have not been learnt well.
2. In the first second, the predicted map is relatively close to the actual map but it slightly misrepresents the intensity of activities in the frontal and occipital regions.
3. The 2nd second, there is improved alignment in the frontal areas but there is some discrepancies in the temporal regions. This suggests that while the model learns the general dynamics, it may not precisely model the temporal evolution of the brain activity.
4. The 3rd second although the model maintains a general grasp of the brain's topographical distribution, it misjudges the intensity and exact locations of peak activities, particularly in the central and parietal areas.

Note: It must be noted that the brain topographical maps do not change as frequently as it is shown in the above data. Since we are dealing with attention span, the brain topographical maps

have been generated using specific frequency bands: theta, beta, alpha and delta. Hence, we can see the variations in contours and colors through the maps. As a result, we are not being stringent while evaluating the model's predictions.

The model in overall does a good job in the predictions. This could be done better on increasing the training time and compute resources required by the model.

Model 2: Conditional GAN implementation



Frame generated at T+0 timestep

Frame Generated at T+15 timestep/ second

This model focused on just next frame prediction at two timesteps: t+0, t+15. The input training data encapsulates the entire brain topographical maps (including all the frequency bands: alpha, beta, gamma, delta, theta). The conditional GAN leads to generation of artifacts during image reconstruction.

https://medium.com/@jctestud/video-generation-with-pix2pix-aed5b1b69f57

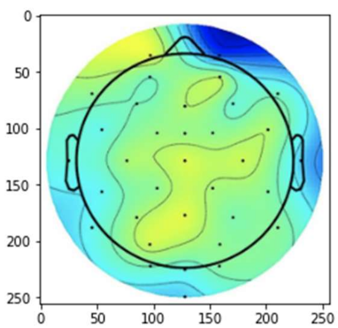
Observation:

1. Artifacts generated in T+0 frame: These are visually distinguishable as irregular, noisy patches that do not conform to the typical smooth gradients seen in brain topographical maps. The discriminator in the cGAN setup might not be sufficiently penalizing these discrepancies during training, leading the generator to produce less accurate outputs. The model might be underfitting due to a lack of depth or insufficient training data to capture the complexity of the brain's activity patterns.
2. The frame generated at T+15 shows an absence of the earlier noted artifacts, indicating a possible stabilization in the model's predictions as it iterates. This could be a result of the model better learning the data distribution with more iterations.
3. Consistency and Smoothness: The image appears smoother and more consistent with what one might expect from brain topographical data, suggesting that the conditional aspect of the GAN (using prior frames as conditions) is helping guide the generation process.

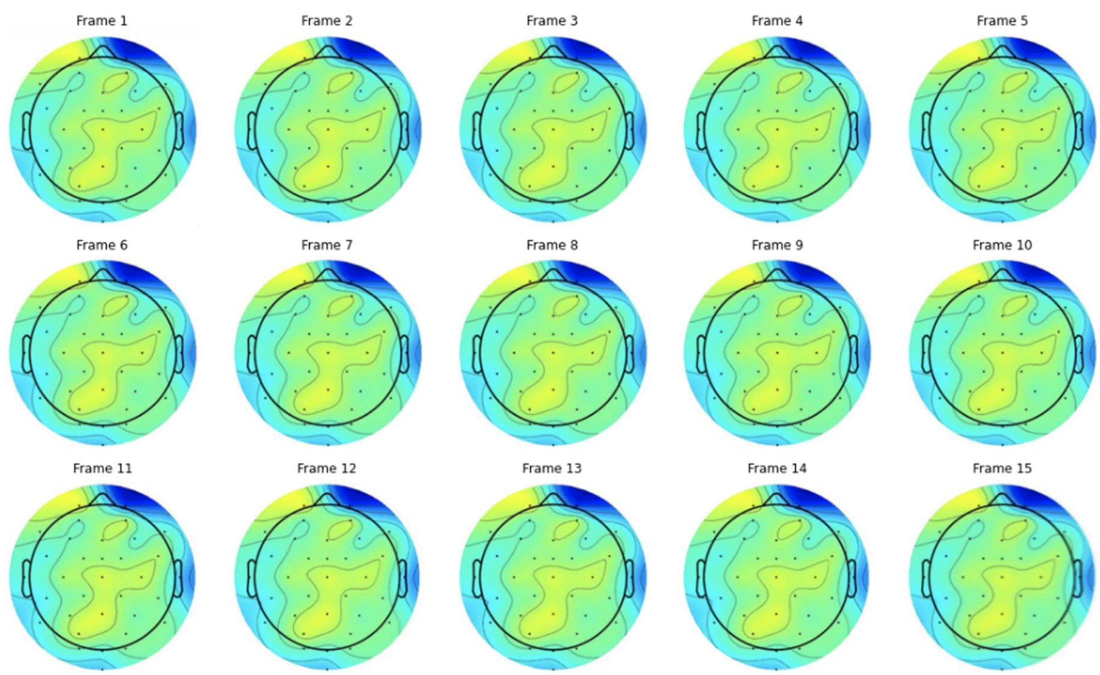
Model 3: Same architecture as Model 1 – only next frame prediction

The same model architecture as model 1, but focuses solely on next frame prediction at a future timestep. Only difference is that, each second consists of 16 frames. Hence, the 512 samples were averaged across 8 frames, to give 16 frames per second.

Input image:



Next frame predictions:

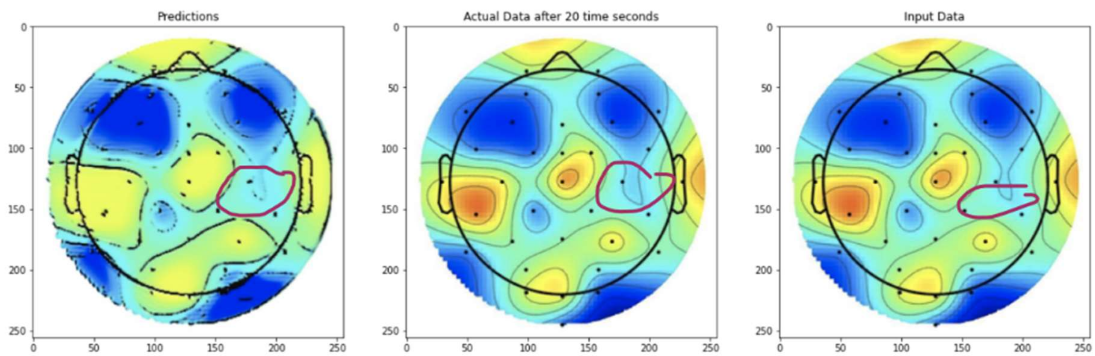


Observation:

1. The general pattern and distribution of activity remains relatively consistent across the frames, hence representing a stable brain state within the given time frame. This stability makes it easier for the model anticipate the future states, given that the changes are only subtle shifts in intensity rather than dramatic changes in the distribution of activity.
2. The model's effectiveness is demonstrated in its ability to handle the slight variations accurately without introducing artifacts or significant deviations from the observed progression.

In order to evaluate how the model performs, we check how the model predicts the brain map after the next 10 timesteps and 20 timesteps.

We observe that the model has difficulty when it is made to predict the brain map after 20 time seconds.



Observations:

1. The model appears to be reasonably effective in capturing the general spatial distribution of brain activity as indicated by the similarity in the broad patterns across the prediction, actual data and input data.
2. The model does not capture the specific area of heightened activity in the temporal region on the left side of the brain. It predicts a more diffused and less intense activity in that area.
3. The actual data shows a concentrated high activity area which the model fails to predict. Instead, it predicts moderate brain activity in that region, suggesting that it could not anticipate a dynamic change in the brain correctly.

Evaluation:

1. Strengths: model is effective in maintaining overall integrity of brain's topographical map.
2. Weaknesses: Model struggles with local precision, particularly in predicting changes in activity intensity.

Areas for improvement:

1. Implementation of more sophisticated neural network architecture
2. Adjustment of hyperparameters, learning rate, number of layers, nodes in each layer to improve model's sensitivity to subtle changes.

References

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4. Applied Sciences | Free Full-Text | Emotional Stress Recognition Using Electroencephalogram Signals Based on a Three-Dimensional Convolutional Gated Self-Attention Deep Neural Network (mdpi.com)