Since face-like visual stimuli undergo specialized processing in human brain compared to other non-face objects (see Kanwisher et al. [12–15]), face images were employed in numerous brain studies particularly studies on attention. The objective of the current work is to develop a clinically convenient and portable neurogranin platform for simultaneously monitoring visual attentional states to two categories of images using brain activity.

a separate aim of this study is to implement an attention training paradigm using solely Python-based code and easy compatibility with consumer-grade EEG equipment with dry electrodes

* The objective of the current work is to develop a Python-based programming neurofeedback platform for simultaneously running an attention training task, recording, analyzing, and decoding EEG, and generating visual stimuli as a feedback.
* Develop a novel closed-loop decoder adaptation pipeline for a neurofeedback based attention training platform
* implement an attention training paradigm using solely Python-based

***Developed BCI Platform***

The BCI platform consists of a wireless EEG headset (Unicorn Hybrid Black, manufactured by g.tec. It has 8 channels located based on 10-20 international systems. The exact locations are labeled sequentially as *'Fz', 'FC1', 'FC2', 'C3', 'Cz', 'C4', 'CPz', and 'Pz'*), a workstation computer with dual monitors (one monitor can be viewed by the experimenter to control the experiment, and the other monitor is positioned in front of the participants for the presentation of stimuli), and the python based developed data acquisition and analysis software.

***An attention training paradigm***

The attention training protocol includes three phases: open-loop pre-evaluation, closed-loop neurofeedback, open-loop post-evaluation. Each phase contains eight blocks. At the start of each block, a text cue is displayed for 5 seconds, instructing participants on the specific task to undertake. In the open loop pre/post-evaluation task, the text cue is the target subcategory (indoor, outdoor, female, and male) to which the participants should respond to by a keypress, while in the closed-loop neurofeedback task, the text cue is the target category (face and scene) to which the participants should just focus their attention.

In the open loop pre/post-evaluation task each block contains 40 trials each includes a composite image with a 50% transparency for each category: scene (indoor or outdoor) and face: (male or female). The duration of each trial is set to one second. During each block, participants watch a sequence of composite images. Thay are asked to identify whether the shown composite image contained the task-relevant image (e.g., an indoor image) or the task-irrelevant image (e.g., an outdoor image) by pushing the trigger button for each recognized relevant image and withhold their responses for irrelevant images. During the open-loop pre-evaluation task, both EEG brain signals and behavioral performance (key presses) are collected. This data is used to develop an individualized attentional classifier to decode a subject's attentional state during the viewing of a composite image and determine the specific category they are concentrating on. The developed decoder is used in the closed-loop neurofeedback phase.

In closed-loop neurofeedback task each block contains 8 trials each includes a composite image starts with a 50% transparency for each category. The duration of each trial is set to five second. Only neural data is recorded during neurofeedback phase. In this task the transparency of each category within the composite image will be updated in every second based on the participant’s decoded attentional level to the target category of the text cue. If participants attended well (high levels of task-relevant information decoded in their signals), the task-relevant image became easier to see, and vice versa. Thus, the feedback works as an amplifier of participants’ attentional state, with the goal of making participants aware of attention fluctuations and hence improve sustained attention abilities.

**3. Classification Methods**

In our preprocessing pipeline for EEG data, several crucial steps were implemented to ensure the optimal quality of the data for subsequent analysis.

Initially, the raw EEG data underwent bandpass filtering using the Butterworth filter, effectively filtering frequencies between 0.4 and 40 Hz. Then any potential artifacts present in the data were identified and removed. Next, the data was denoised using a KNeighborsRegressor model to improve the signal-to-noise ratio.

Our study employed a comprehensive feature extraction technique on EEG signals to capture essential electrophysiological markers.

We segmented every 250 samples into one epoch, corresponding to a duration of 1000 milliseconds, which is the time each image is displayed on the monitor. Get So we get 320 epochs, (8 blocks each has 40 images)

We identified specific Event-Related Potential (ERP) components within designated time windows: N180 (160-200ms), P300 (280-320ms), N500 (480-520ms), N600 (580-620ms), P700 (680-720ms), and P900 (880-920ms). For each window, we extracted the mean amplitude as an ERP feature (a feature vector with the size of (6x8) for each epoch). We decomposed the EEG data into specific frequency bands: delta (0.5-4Hz), theta (4-8Hz), alpha (8-14Hz), beta (14-30Hz), and gamma (30-40Hz). For each band, we computed the mean power and applied the Hilbert transform to obtain the amplitude envelope of the signals (a feature vector with the size of 40 (5x8) for each epoch). After concatenating all the extracted features into a feature matrix (320, 8, 16), we shuffled its order, allocating 90% for SVM model training and the remaining 10% for model testing.

Utilizing preprocessed signals, we condensed each epoch from 250 to 50 by averaging every five sequential data points. This compacted representation maintained vital signal features. Then, we averaged across all blocks, producing a signal for each channel that represents the average neural response to the stimuli.

These extracted features, comprising power metrics, Hilbert features, and ERPs, were combined across channels to create a holistic feature matrix for each epoch, providing a multidimensional representation of the EEG data.

The image trials consisted of composite face and scene images that were displayed for 1 s. The first task run only contained blocks with acquisition trials, that is, an equal mixture of faces and scenes for each image (see Figure 1b

blended images of “face” and “scene” is shown in a sequence of trials and the behavioral responses to primed categories are collected using push buttons. Participants were asked to pay attention to a subcategory of faces or scenes in a sequence of composite images (e.g., a mixture of 50% of an image of a female face and 50% of an image of an indoor scene).

During neurofeedback task, the subject is asked to control the blurriness and transparency of a face or scene image in the blended image (as feedback reward/punish) by using his/her neural activities (Fig. 5). Only neural data is recorded during neurofeedback phase.

A Graphic User Interface (GUI) was developed to allow a practitioner to conveniently administer the experimental protocol.

We propose to implement a protocol consisting of eight blocks of trials with a respite between blocks. Each block starts with a five-second texture cue instructing the attended subcategory image, followed by 40 trials of image stimuli.

We first setup a real-time BCI system to collect EEG signals and behavioral responses in a synchronous way.

Stimuli. Images consisted of grayscale photographs of female and male faces and indoor and outdoor scenes that were combined into composite stimuli by interpolating two images using a variable interpolation factor (α). All image trials were generated from an interpolation of two randomly drawn images, choosing from 1000 images for each subcategory, for a total of 4000 unique images. s were collected through the Internet.

2.2.2 Participants. four healthy adults (mean age = 25, age range = 22–35)

All participants provided written informed consent to a protocol approved by the …. Department of ….. (approval number: IP-IRB / 26112018) .

2.2.4 Experimental Procedure. All participants completed two behavioral sessions and one neurofeedback session all in one days. The first task is a behavioral pretraining session with two runs of the sustained attention task without recording of EEG. The second day was an EEG session consisting of a single run with stable, acquisition stimuli as in the pretraining session and five runs with real-time neurofeedback. The third day was a behavioral posttraining session with two runs of the attention task without recording of EEG, similar to the first day.

Ninety percent of the images (45 images in each block) contained the target category and required a keypress response, while 10% (5 images in each block) contained the nontarget category to which responses had to be withheld (lure trials).

For each task run, four of eight blocks involved attending to faces, and the remaining four blocks involved attending to scenes. To avoid an unbalanced category distribution, the target categories were randomly assigned to each block with the constraint that two blocks of each target category had to be present within the first and last four blocks.

The target subcategories presented for each participant throughout the three-day experiment were held constant, so if the target categories were indoor and female for a particular participant during the pretraining session on day 1, the participant would be primed to the same categories on the following days. The category assignment for each participant was random but counterbalanced across all participants. Since the task runs contained randomly generated target categories and composite image trials, each run was unique to avoid a habituation and recognition effect. For behavioral sessions during the pretraining (day 1) and posttraining (day 3) sessions, all participants completed two task runs of eight blocks (total of 800 trials). For these behavioral sessions, all composite image trials had an equal mixture proportion of face (50%) and scene (50%). During both the behavioral and EEG sessions, participants were given 30 s breaks after four blocks. The total experiment time was 17 min for the behavioral session and 52.6 min for the EEG session, including breaks, text cues, and fixation time. For each of the three sessions, participants were instructed to sit relaxed in a chair with their right hand resting on the table with a finger on a keyboard to provide behavioral responses. Participants were instructed to keep their eyes focused on the fixation cross on the screen. Prior to the EEG session, participants were asked to avoid excessive movements during stimuli presentation. They were informed that the feedback trials would be updated based on their attention toward the target category and not based on their keypress response. Specifically, the task-relevant image would become easier to see if they were paying attention and harder to see if their attentional level was decreasing. For the pretraining and EEG sessions, participants were shown short examples of, respectively, the behavioral experimental paradigm and neurofeedback paradigm. All instructions were scripted and identical across participants.

This study is a one-time visit and single session study that takes about 2 hours

You will be asked to sit in a chair in a comfortable position and relaxed body while observing a computer screen in a distance (at least 50 cm away). You will be asked to wear our EEG cap system on your head. Then, we will continue with the following phases. We will have three phases for our experiment to finish.

Pre-evaluation:

We use a model for attention training in which blended images of “face” and “scene” are shown in a sequence of trials. The behavioral responses to the instructed category are collected using push buttons. Each blended image is shown for one second. Across trials and following initial instructions, you will push different keys using your hands in response to the observed images.

Phase 2: Neurofeedback

During neurofeedback task, you are asked to control the blurriness and transparency of a face or scene image in upcoming blended images by using your brainwaves. The initial instruction for an image category will be given.

The wavelet transforms, a versatile tool for signal analysis, has been integrated into the EEG feature extraction process. Unlike Fourier-based methods that provide frequency information without temporal localization, wavelet transform can capture both time and frequency characteristics of a signal. Specifically, for each segment of denoised EEG data, we iterate over every channel and subsequently each frequency band. Post band-pass filtering using the designated frequency band, we apply a wavelet decomposition using the 'db4' or Daubechies wavelet with four coefficients. This decomposition yields several sets of coefficients, each representing the signal's detail at a particular scale or resolution. After concatenating these coefficients, we compute their amplitude. For each coefficient set, we derive statistical measures—mean, variance, skewness, and kurtosis—of the amplitude values. These metrics collectively offer insights into the distribution and shape of the wavelet-transformed data. The process results in a comprehensive feature set for each EEG segment, amalgamating time-frequency wavelet characteristics with other features for subsequent analyses.

We employed a dynamic buffer in our real-time EEG data processing framework to capture and manage incoming EEG samples. The buffer was initialized to hold a 5-second window of data, translating to 1,250 samples given our sampling rate of 250 samples per second. This buffer matrix has dimensions of 1,250 by 8, reflecting the eight EEG channels. During data acquisition, EEG data is fetched for each of the eight channels and is reshaped and stored for further processing. This data is sequentially appended to the buffer every second, ensuring a continuous stream. Any excess data beyond the buffer's 5-second capacity is trimmed off to maintain the buffer's size constant.

In the real-time EEG data processing pipeline, a Butterworth bandpass filter is employed to selectively retain frequencies of interest while attenuating those deemed irrelevant. For the initial data buffer, the filter's state is not predefined; therefore, the filter initializes its state based on the first data point it encounters. This ensures a continuous and smooth transition, crucial for real-time data. As subsequent data buffers are processed, the filter utilizes the final state from the previous buffer as its initial state for the next. This method ensures continuity in the filtering process across buffers, minimizing abrupt changes or distortions, which can occur when filtering non-continuous data segments separately. This stateful filtering approach ensures that even as new data comes in, the filtering remains consistent and seamless.

Following this, artifact rejection techniques are employed to eliminate any spurious or unwanted signals. After the artifact rejection, we further enhance the data quality through specialized denoising procedures. Processing in this sequential manner — filtering, then artifact rejection, and finally denoising — leverages both historical and current data, resulting in more effective noise and artifact removal.

Once the buffer is updated and processed, the most recent chunk of data is extracted for feature engineering. These features are then utilized to predict the individual's attentional state in real-time."

Using the developed decoder, the subject's attentional state is determined. If the prediction aligns with the given instruction, the transparency of the designated category in the composite image increases; if not, it decreases. This visual feedback provides the subject with an awareness of their attention level and encourages them to remain focused on the instructed category.

After each block, we incorporate the data into our data collection, retrain the model, and then utilize the newly trained model (decoder) for the subsequent block.

Employed a dynamic buffer for real-time EEG data processing (initialized to hold 5 seconds of data, 1,250 samples, size: 1,250 x 8 )

During acquisition, EEG data is fetched for each channel, and data is appended to the buffer every second.

Excess data beyond the 5-second capacity is trimmed to keep buffer size consistent.

Buffer updated and processed for real-time data.

Employed a Butterworth bandpass filter in the EEG processing pipeline.

The initial filter state is set based on the first data point for smooth transitions, subsequent buffers use the final state from the previous buffer as the initial state, which ensures continuous and consistent filtering across buffers.

Followed by Artifact rejection and denoising procedures.

The most recent data chunk was extracted for feature engineering.

Features used to predict the individual's real-time attentional state using the developed decoder

Correct predictions increase image transparency; incorrect ones decrease it.

Visual feedback offers awareness of attention level and encourages focus.

Post-block: Data added to collection, model retrained, and new decoder used for next block.

In the study, a multi-layer perceptron (MLP) classifier from the scikit-learn library is fine-tuned using the Optuna hyperparameter optimization framework. The goal of this optimization is to ascertain the optimal neural network architecture and learning parameters. For each trial, the number of hidden layers is selected from a range between 1 and 4, and for every such layer, the number of neurons is chosen from a span of 16 to 512. The activation function for the hidden layers can be one of four types: ReLU, logistic (sigmoid), hyperbolic tangent (tanh), or identity. It's important to note that in scikit-learn's MLP implementation, the activation function for the input layer is linear (i.e., no activation), and for binary classification problems, the output layer uses a logistic (sigmoid) activation, whereas for multi-class problems, a softmax function is employed. The learning rate initialization is sampled logarithmically between values of 1e-4 and 1e-1, and the upper limit on the number of iterations set for model training lies between 50 and 1000. The model's efficacy is gauged using its accuracy on a separate validation set. After conducting 70 trials, the results highlight the architecture and hyperparameters that deliver the highest accuracy, underscoring the effectiveness of both the model and the optimization approach.

* Utilized the scikit-learn library to implement a multi-layer perceptron (MLP) classifier.
* Employed the Optuna framework for hyperparameter optimization to fine-tune the MLP architecture and learning parameters.
* Selected the number of hidden layers from a range of 1 to 4 in each trial.
* Choose the number of neurons for each hidden layer from a span of 16 to 512.
* Possible activation functions for hidden layers: ReLU, logistic (sigmoid), tanh, or identity.
* The input layer uses a linear activation (no activation), and the output layer employs a logistic (sigmoid) activation for binary tasks and softmax for multi-class tasks.
* The learning rate initialization is logarithmically sampled between 1e-4 and 1e-1.
* Set the maximum iterations for model training from a range of 50 to 1000.
* Evaluated the model's performance using accuracy on a validation set.
* Conducted a total of 70 optimization trials to determine the best architecture and hyperparameters.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **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 |

**Feedback Generator**

**SVM Prediction**

|  |  |
| --- | --- |
|  | **Processed**  **Data Collection** |

**v**

**Check Instruction**

**Transparency Adjustment**

**SVM Recalibration**

**Envelop Hilbert**

**ERP**



**Human Subject Workstation**

A person wearing a virtual reality headset sitting at a desk with a computer

Description automatically generated with low confidenceA person wearing a black helmet

Description automatically generatedA graph of colorful lines

Description automatically generated with medium confidenceA black background with white text

Description automatically generatedA person with a mountain in the background

Description automatically generated with low confidenceGraphical user interface, text

Description automatically generated with medium confidenceA picture containing wall, indoor, person, person

Description automatically generated

**SVM**

**SVM Initialization**

**Pre-evaluation**

**Feature Extraction**

**EEG**

* **Bandpass**
* **Denoise**
* **Artifact Rejection**

**Stimulus**

**Instruction**

**Composite Image**

**Preprocess**

**Pre-Evaluation**

**Neurofeedback**