Three healthy participants including 2 males and 1 female, with a mean age of 29 years, voluntarily completed eight training blocks of the experiment. All participants had normal or corrected-to-normal vision. All participants gave written consent to the experiment. The computerized task was provided by a PC with dual monitors. One monitor was viewed by the experimenter to control the experiment. The other monitor was positioned in front of the participants for the presentation of stimuli. The participants were asked to sit comfortably in a fixed chair with one hand resting on the lap and another hand ready to press a key to give behavioral responses. The participants were instructed to pay attention to the monitor during the experiment and limit their excessive body movement. The participants were also asked to fixate their gaze on the middle of the screen and keep their heads at approximately 50 cm from the monitor while observing the stream of images.

Our experimental protocol consisted of eight blocks of trials with a 10-second respite between blocks. The experiment starts with 3 minutes just recording to make sure that the EEG signals are settled, followed by eight blocks of trials. Each block started with a five-second texture cue instructing the attended subcategory image, followed by 5 seconds of a black image, 2 seconds of a grey image with just a cross sign in the middle of the image (considered as a baseline data) followed by 40 trials of image stimuli. The duration of each trial was set to one second without any intertrial time. A trial includes a greyscale overlaid picture in which 50% of opacity was from the scene (indoor or outdoor) category and 50% was from the face (male or female) category. There was no repetition of face or scene images through each block of the experiment. This process helped to prevent any learning mechanism from happening for the participant. Participants were asked to identify whether the shown image contained the task-relevant image (e.g., an indoor image) or the task-irrelevant image (e.g., an outdoor image) by responding to each superimposed image. They were asked to press the key on the keyboard for each recognized relevant image and withhold their responses for irrelevant images. The task-relevant subcategory images were fairly distributed within each block. As a result, 90\% of the composite images contained images from the task-relevant subcategory (e.g., indoor image) while the other 10\% of the composite images contained images from the task-irrelevant subcategory (e.g., outdoor image).

Table 1 illustrates a sample sequence of composite images during a block and also the corresponding expected responses from participants. we ran the experiment three times to get more trials. The total time for each experiment was about 25 minutes per participant.

In the present work, we aimed to identify participants’ attentional states into two categories of images (face versus scene; regardless of their subcategories) by using recorded EEG signals. The participants were primed with the sub-categories throughout the experiment. So, we hypothesized that the brainwaves contained common features for the subcategories of one category. This assumption reduced the problem of the classification of EEG signals to a 2-class classification problem, i.e., classifying underlying patterns of EEG while the participants attended to faces or scenes. Meanwhile, the behavioral responses were collected and used as a predictor for comparison (relevant image vs. irrelevant image; see Table 1). Flowcharts in Figure 2 illustrate the process of analyzing a participant’s overt response as well as his/her EEG signals. A brief description of EEG signal preprocessing, features extraction, dimensionality reduction

3.2. Temporal Features Extraction. Numerous features can be extracted from EEG data. After an initial investigation, we found that there are multiple ERPs associated with different stages of attention.

Attention is the ability to facilitate processing perceptually salient information while blocking irrelevant information to an ongoing task. For example, visual attention is a complex phenomenon of searching for a target while flattering out competing stimuli. In the present study, we developed a new Brain-Computer Interface (BCI) platform to decode brainwave patterns during sustained attention in a participant. Scalp electroencephalography (EEG) signals using a wireless headset were collected in real-time during a visual attention task. In our experimental protocol, we primed participants to discriminate a sequence of composite images. Each image was a fair superimposition of a scene and a face image. The participants were asked to respond to the intended subcategory (e.g., indoor scenes) while withholding their responses for the irrelevant subcategories (e.g., outdoor scenes). We developed an individualized model using deep learning techniques to decode the attentional state of the participants based on their brainwaves. Our model revealed the instantaneous attention towards face and scene categories. We experimented with three volunteer participants. The average decoding accuracy of our model was about 85%. The present work was an attempt to reveal the momentary level of sustained attention using EEG signals. The platform may have potential applications in visual attention evaluation and closed-loop brainwave regulation in the future.

After wavelet transformation, the EEG data was segmented into epochs. Epoching refers to dividing the continuous EEG signal into shorter, fixed-length segments. These segments (or epochs) were then used for further analysis. In our case, the epoch size was set to 250 data points, corresponding to one-second intervals given the sampling rate. This epoch size was chosen to capture sufficient temporal resolution while maintaining manageable data sizes for analysis.

Baseline normalization was the next critical step. For this, we first identified segments of the EEG data representing baseline brain activity – periods with no external stimulation or event-related activity. The mean power of these baseline epochs was calculated. This mean baseline value was then used to normalize the power values in the activity epochs – the epochs corresponding to specific events or stimuli. This normalization process involved dividing the power values in each activity epoch by the mean baseline power. This step is crucial to control for inter-trial variability and enhance the comparability of epochs across different trials and conditions.

Finally, we calculated the mean power over each block of data and across all blocks. Within each block, the mean power across all epochs was computed, providing a summary measure of the EEG activity for that block. This step was repeated for each frequency and each EEG channel, resulting in a comprehensive matrix of mean power values. Furthermore, to obtain an overarching view of the EEG activity across the entire experiment, we calculated the mean power across all blocks. This provided us with a grand average, reflecting the consistent patterns of brain activity throughout the study."

In our study, the Morlet wavelet transform was employed for the analysis of EEG data. This process began with the generation of a Morlet wavelet for each frequency within the predefined range (0 to 40 Hz, in 2 Hz steps). The number of cycles for each wavelet varied linearly from 1 to 10, enabling a balanced time-frequency resolution tailored to each frequency. Each Morlet wavelet was then convolved with the EEG data. This convolution process isolated the frequency-specific components of the EEG signals, resulting in a time-series representation of the power for each frequency.

Following the Morlet wavelet transformation of EEG data, we proceeded with epoching, which involves dividing the continuous EEG signal into shorter, fixed-length segments or epochs. Each epoch consisted of 250 data points, equivalent to one-second intervals given our sampling rate.

Crucially, within each data block, epochs were categorized into two distinct sets: 'base' and 'activity.' The 'base' epochs were identified as periods representing baseline brain activity. Conversely, 'activity' epochs corresponded to periods where specific events or stimuli were presented. This separation was essential for subsequent baseline normalization and analysis of stimulus-specific brain activity.

For each block, the mean power of all 'base' epochs was computed, resulting in a single, average baseline signal. Similarly, an average signal for the 'activity' epochs was obtained by calculating the mean power across these epochs. This process effectively distilled the complex EEG data into two representative signals per block, one reflecting baseline brain activity and the other depicting brain responses to stimuli or events.

In the crucial step of baseline normalization, we focused specifically on the first 200 data points of the mean 'base' signal. This subset of the baseline was used to normalize the 'activity' signal, thereby controlling for variations in baseline brain activity across trials and conditions. The normalization involved dividing the power values in the 'activity' signal by the mean of these first 200 baseline data points. This targeted approach to normalization ensured that the resultant activity epochs were adjusted relative to a consistent baseline measure, enhancing the reliability and comparability of our findings across different blocks and conditions.

Finally, we calculated the mean power over each block and across all blocks for both 'base' and 'activity' epochs. This aggregation provided a comprehensive view of the brain's baseline state and its response to stimuli, pivotal for our study's analysis and conclusions."

In this study, we focused on the development and implementation of a Brain-Computer Interface (BCI) system for analyzing visual attention using EEG signals. This involved using a wireless EEG headset, workstation computers, and a novel Python-based software for data collection and analysis. The study participants were exposed to a series of visual stimuli while EEG data was collected. Signal processing techniques including bandpass filtering, artifact rejection, denoising, epoching, and Independent Component Analysis (ICA) were used to ensure signal quality. Results show the effectiveness of the BCI system in distinguishing between attentional states towards different image categories. The results showed distinct neural responses to faces and scenes, with significant components such as N200, P300, and N600 indicating differential engagement with stimuli. A time-frequency analysis using Morlet wavelet transform further confirmed these findings. An individualized Multi-Layer Perceptron (MLP) classifier was developed for each participant, achieving an average decoding accuracy of approximately 85%, demonstrating the efficacy of the tailored models.

the recorded signal that decodes attention-related brainwaves using EEG during a visual task, requiring participants to discern and respond to specific composite images. Analysis of ERP and wavelet transforms exposed distinct neural patterns to different stimuli and temporal brain activity, respectively. A deep learning model was crafted for individual attention state decoding, achieving an 85% average accuracy across three subjects, paving the way for applications in attention assessment and brainwave modulation systems.

This study presents a BCI platform that records EEG signal while running a visual attention training task which is displaying composite images that are a combination of face and scene image. Subsequently, erp and wavelet transform is applied on the collected signal to explore any possible and distinguishable patterns in brain wave toward face and scene images. Finally a multy layer perceptron classifier developed and optimized for each individual.