Auditory Brainwave Entrainment System using Time-Series Analysis of EEG Signal

Simrat Kaur, Rajesh Kumar Krishnan, Xinrui Yu, and Jafar Saniie
Embedded Computing and Signal Processing (ECASP) Research Laboratory (http://ecasp.ece.iit.edu)
Department of Electrical and Computer Engineering
Illinois Institute of Technology, Chicago IL, U.S.A.

***Abstract*—This paper is focused on improving people's general inability to quality sleep. We designed a feedback system that can process brainwaves in the form of time-series EEG data and convert them into RGB color-coded based topological map-like images. The system then uses CNN architecture based on 2D convolution with ReLU activation functions and dense layers for image and frequency classification to detect the EEG frequency and then based on the concept of brainwave entrainment, produce binaural tunes at required slower frequencies, to help to relax and slowly move the brain activity spectrum down to delta waves, which ranges around 0.5 - 4 Hz. The feedback signals create a gradual shift in the received frequency, thereby entraining the mind to tend towards the desired slower brainwaves. The testing was performed on Jetson Nano and the resulting accuracy tested for RGB-based frequency classification was over 80% which led to a successful binaural tone generation to create a slow auditory output wave, thereby eventually increasing the delta activity in the brain.**

Keywords—Sleep, EEG, Brainwave, Artificial Intelligence, Sleep disorders.

I. Introduction

About 50-70 million US adults have a sleep disorder [1], and it is noted that prolonged or even acute deprivation of good quality sleep can disturb a person's concentration and memory, cause cognitive impairment, and various other critical mental and physical health disorders. Sleep is defined as a period of rest for the physical body and the mind for a few hours, mostly at night, wherein the nervous system is considered inactive, and consciousness is temporally suspended while still sensitive to external stimuli [2]. Sleep disorders on the other hand are defined either by physical or emotional problems which affect the quality, quantity, and timings of sleep. The natural circadian rhythm may be disrupted and there may be daytime distress among several other symptoms. Insomnia is regarded as the most common disorder as around one-third of the adults in the US report its symptoms [3]. Considering we spend a third of our lives sleeping, it plays an integral role in our general wellbeing.

To demonstrate our results for the paper, we designed a feedback system where the inputs are raw EEG signals which first undergo time-series analysis, and then various classes of frequency are determined. For this paper, we used three classes for classification namely alpha, beta, and theta. These classified frequencies are then used for topological mapping and generating classified EEG images for each frequency class. The images are processed within a CNN network for performing high accuracy image recognition which can then be used as an input starting point for tone generator to produce the required spectrum of binaural tunes. The various terminologies and concepts related to sleep are briefly discussed below.

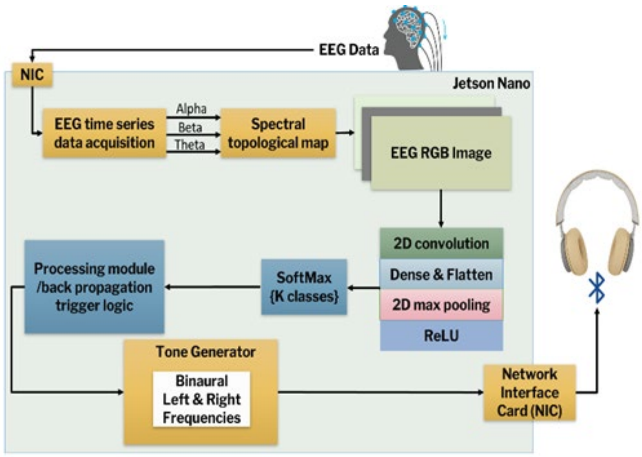

Fig. 1. Auditory Brainwave Entrainment System Diagram

II. Basis of Sleep Cycles

A classic night's sleep consists of two types of sleep cycles, namely Rapid Eye Movement (REM) sleep and four non-REM (NREM) sleep cycles [4] [5] [6].

A. NREM

- Stage 1: It consists of alpha activity in the brain i.e., 8 Hz to 12 Hz of frequency. N1 Sleep is the transition from wakefulness to sleep. During this short period, which lasts for several minutes of light sleep, heartbeat, breathing, and eye movements slow and the brainwaves slow down from their daytime wakefulness patterns.

- Stage 2: It consists of theta activity in the brain i.e., 4 Hz to 7 Hz of frequency. This is the stage where we enter deeper sleep. Heartbeat and breathing slow down and postural muscles relax even further. The body temperature drops and the eye movements stop. Brain wave activity slows but it is marked by brief bursts of electrical activity.

- Stage 3: It consists of starting point of delta activity in the brain i.e., 0.5 Hz to 3 Hz of frequency. This occurs in longer periods during the first half of the night. The heartbeat and breathing slow to their lowest levels during sleep. The muscles relaxed, and it is difficult to wake during this stage. Brain waves become even slower and hence it's also called slow-wave sleep.

- Stage 4: It consists of more than 50 % of delta activity in the brain i.e., 0.5-3 Hz of frequency. It is the deepest and dreamless state of sleep. The muscles are relaxed, and it will make it difficult to get awaken during this stage. Brain waves become even slower.

B. REM

During this stage, eyes move rapidly from side to side behind closed eyelids. Mixed frequency brain wave activity becomes closer to that seen in wakefulness. The breathing becomes faster and irregular, and the heart rate and blood pressure increase to near waking levels. This is the dreaming stage of sleep and so limbs become temporarily paralyzed preventing the person from acting out of the dreams [5].

As shown in Fig. 2, Each cycle has a distinct associated frequency and timespan, and mimicking these, we can replicate a brainwave pattern through auditory entrainment.

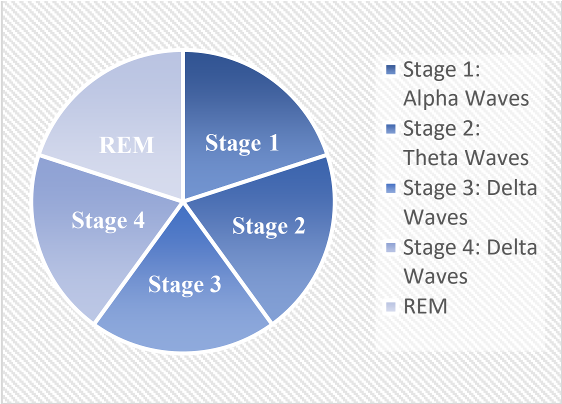

Fig. 2. Stages of Sleep

III. EEG and Brainwave Entrainment

A. Electroencephalogram (EEG)

An EEG is used to capture and monitor the electrical activity of the brain. It uses small electrodes which are placed on the scalp and collects the small impulses and amplifies them as the original electrical impulses in the brain are weak signals. For this study, we used the Neurosky EEG headset. There are different ways in which electrodes can be placed on the head depending upon their number and positions like 10/20 and 10/10, etc.

B. Frequencies recorded in different sleep cycles with EEG

The following are the waves that can be distinguished from the EEG trace [7].

- Beta Waves: These have a frequency range from 13-15 Hz to 60 Hz and an amplitude of around 30µV. This stage indicates Awake Condition.
- Alpha Waves: Indicate the frequency range from 8-12 Hz and amplitude of 30 to 50 µV. These waves indicate the Awake condition only but with the eyes closed or relaxing or meditating.
- Theta Waves: Indicate the Frequency Range from 3 – 8 Hz and amplitude of 50 to 100 µV. These waves are associated with memory and emotions.
- Delta Waves: Indicate the Frequency range from 0.5 to three or four Hz and 100 to 200 µV in amplitude. These waves were observed when we were in deep sleep.
- Gamma Waves: Gamma Waves indicate the frequency range from 30Hz and above. These are the fastest brain waves produced for active concentrated work. [5]

C. Brainwave Entrainment

Brainwave entrainment (BWE), also referred to as brainwave synchronization and neural entrainment, refers to the hypothesized capacity of the brain to naturally synchronize its brainwave frequencies with the rhythm of periodic external stimuli, most commonly auditory, visual, or tactile.

It is believed that patterns of neural firing, measured in hertz, correspond with states of alertness such as focused attention, deep sleep, etc. It is hypothesized that by listening to these beats of certain frequencies one can induce a desired state of consciousness that corresponds with specific neural activity, such as studying, sleeping, exercising, meditating, doing creative work, and so on.

IV. Method Used for Brainwave Entrainment

The resource usage of the brainwave entrainment system is shown in Table I.

A. Effects of auditory input on brain waves

This works on the concept of Brainwave Entrainment. When the ear picks up a slightly different pitch, the brain tries to compensate and finds a frequency somewhere in the middle. This causes both the hemispheres of the brain to harmonize their brain waves, called neural entrainment. Binaural Beats are the special sounds perceived when two auditory stimuli of different frequencies are presented to each ear. When the two tones that are close in pitch, but not identical are sent to a different ear, the brain creates interference that is called the binaural beat without any physical interaction between the waves. These Binaural beats are also called Digital Drugs, as these are the sounds that are capable of changing the brain wave patterns and inducing an altered state of consciousness similar to the effect that happens when drugs are taken or when achieved a deep stage of meditation. [8] [9]

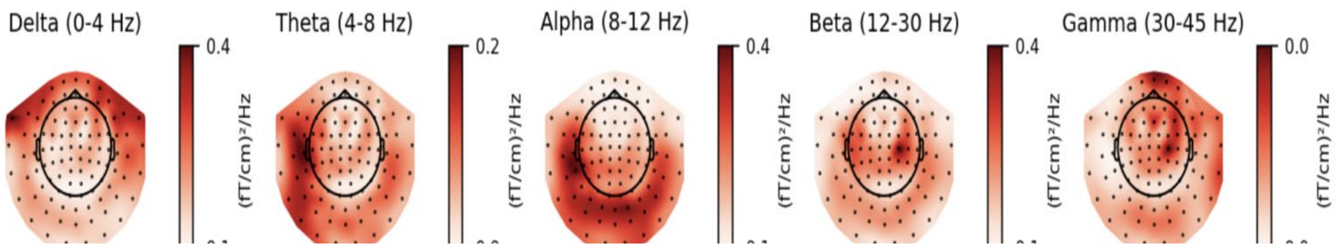

Fig. 3. Brainwaves and their frequencies extracted using MNE library

TABLE 1. RESOURCE USAGE OF THE SYSTEM

Resource Usage			
Hardware		*Software*	
Human Machine Interfaces	Neurosky EEG headset, Headphone	**Programming Language**	Python
Processing Elements	Nvidia Jetson Nano	**Libraries**	Scipy, OpenCV, MNE, Keras
Interface Element	Network Interface Card (NIC)	**Activation Function**	ReLU
I/O peripherals	External monitor, keyboard, mouse, etc.	**CNN Layers**	Convolution, Batch Normalization and Max Pooling

B. Binaural Tones

Binaural tunes are like auditory illusions [10] in the brain. They are perceived at a resultant frequency which is derived from a difference in input auditory frequencies from both the ears. Say, if a person listens to 150 Hz sound in the right ear and 140 Hz sound in the left ear, the perceived audio, that the person would hear would be 10 Hz [10], shown in Fig. 4.

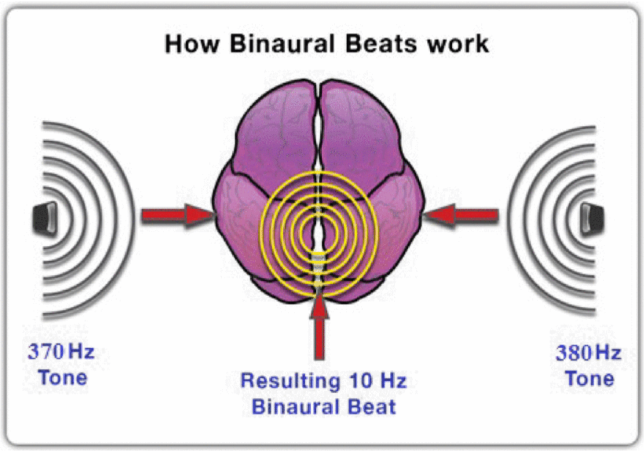

Fig. 4. Perception of binaural tune in our brain. [10]

C. Methods and Stages of Execution

The project was executed in the following steps using the MNE library for data collection and processing of EEG signals. By using Jetson Nano, it is possible to use parallelization to save processing time. These signals were then classified into 3 types- alpha, beta, and theta and were then used in a feedback loop for generated a binaural tune to trigger a decrease in the EEG frequency metric, as shown in Fig. 5.

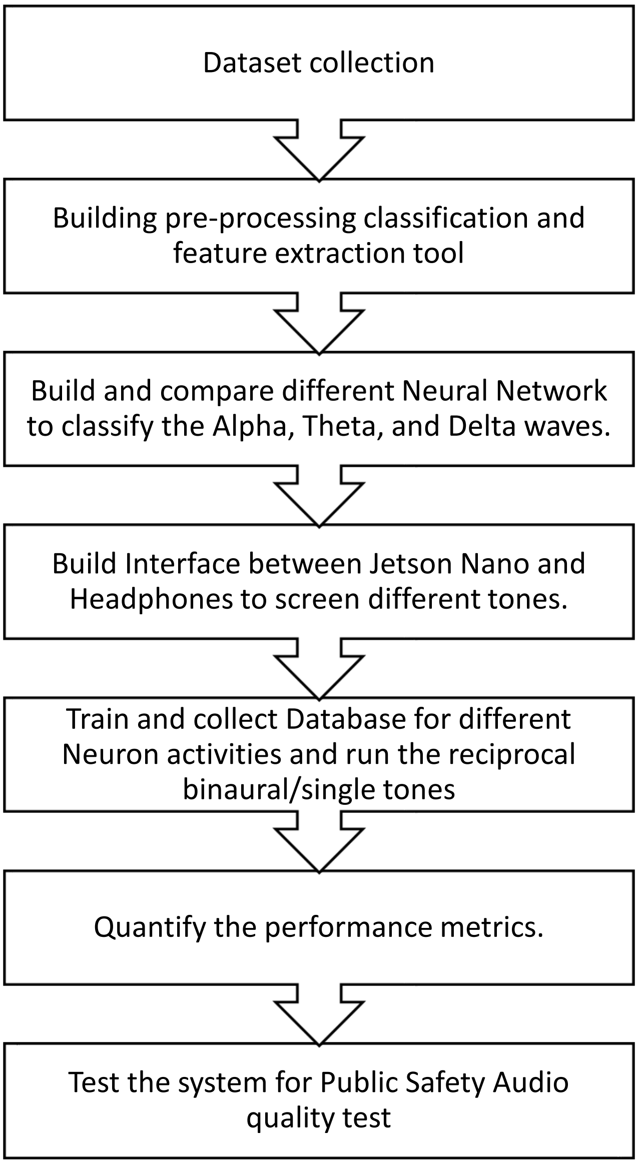

Fig. 5: Execution Stages

V. RESULTS AND DISCUSSION

A. Development of a classifier that can identify and visualize the EEG signals

- **Loading and plotting raw the data set:** A preliminary raw EEG dataset was loaded and displayed in a simple plot for initial visualization. Since there was extensive data processing and classification, we used the MNE library to create an interactive tool to help with navigation and user interactions during the process. The raw data loading log and the graphical representation of the raw data are shown in Fig. 6.

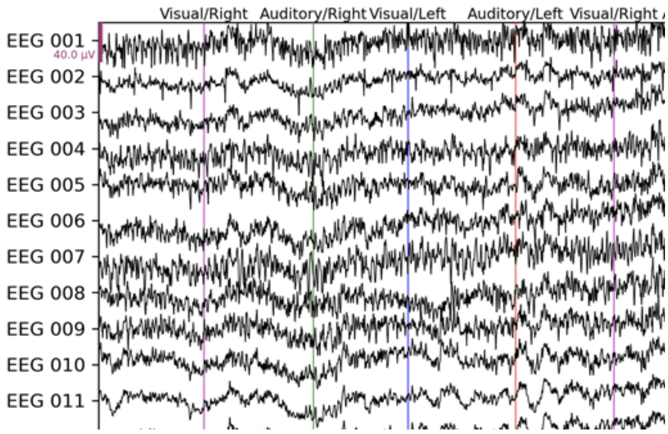

Fig. 6. Raw & unfliltered EEG data (100 seconds) with STIM event annotations

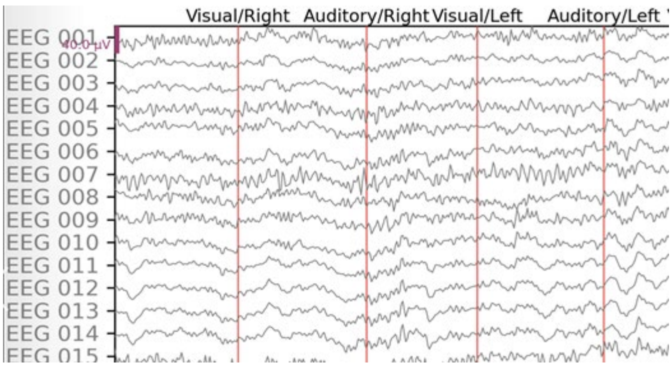

Fig. 7. Cropped (50 seconds) and filtered (0.1 to 40 Hz) EEG data with STIM event annotations

- **Event annotation for STIM Channel:** STIM stands for stimulus channels that are time-locked to specific events like an external stimulus or even a button press. Notice the blue markers on the EEG plot below (Fig. 9), these are the point of events that are marked with specific event ID (see Fig. 9) to understand the plot better and differentiate signals in the graph [11].

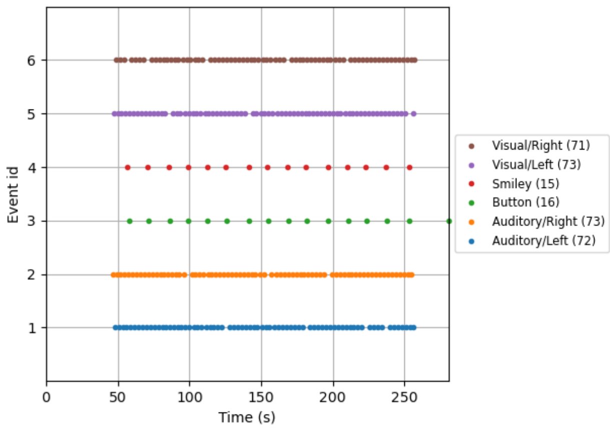

Fig. 8. Color coded stimulus event IDs with number of stimulations shown in parentheses

- **Crop and filter out the data to present a raw plot with unfiltered and filtered data:** Data filtering and cropping were performed by setting a band-pass filter from 0.1 Hz up to 40 Hz in a frame size of 100 ms. The filter uses a hamming window with 0.0194 passband ripple and 53 dB stopband attenuation. This filtered data is used for further processing and is used for the PSD plotting, which is discussed below. Compare Fig. 7, unfiltered (left) and filtered (right) for raw graphs with STIM event markups.

- **PSD with live visualization:** The power spectral density (PSD) describes how the power of a continuous signal or time series is distributed over frequency. This is an underlying FFT process to transform data for each frame from the time domain to the frequency domain. Power spectral density is commonly expressed in watts per hertz (W/Hz) [12]. Here, plotting the PSD using the MNE Library functions gives us insight into various signal capabilities in heatmap-like output images over our specified frequency spectrum collected in our EEG signals, as shown in Fig. 8. Note that the tools have been created to extract, filter, and visualize the EEG time series data.

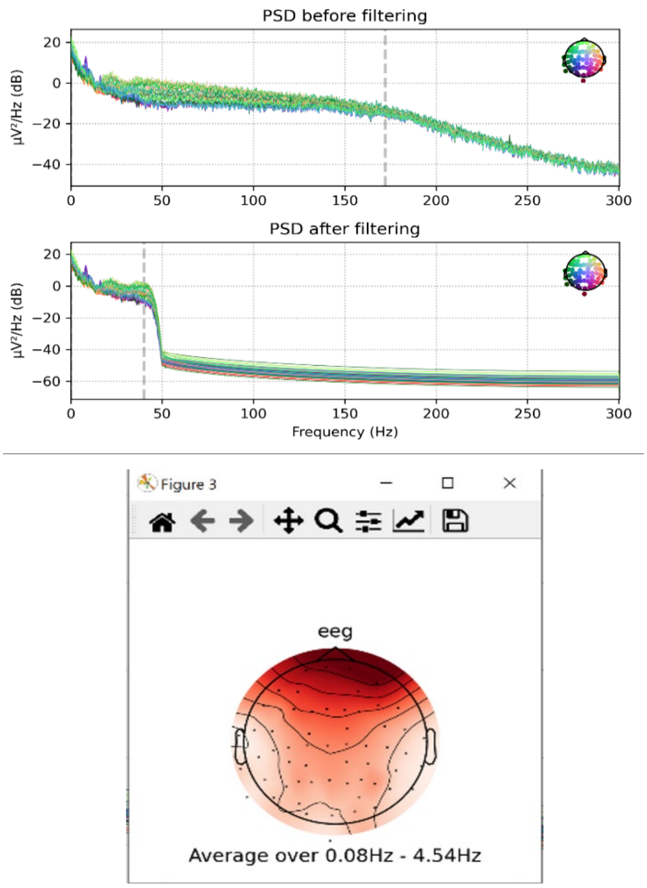

Fig. 9. PSD plot for filtered and unfiltred data with a sample topological map of brainwaves during delta activity of upto 4.54 Hz

- **Convert the dataset to BIDS library for organizing and visualizing:** There hasn't been enough development of consensus and data standardization in this area. Hence a little structuring and organization of data are necessary to help people understand and make fair use of the data. We have used Brain Imaging Data Structure (BIDS) library to organize our data. BIDS was heavily inspired by the format used internally by the OpenfMRI repository that is now known as OpenNeuro [8].

- **Extract the evoked with the right condition:** Evoked data are obtained by averaging epochs. Typically, an evoked object is constructed for each subject and each condition, but it can also be obtained by averaging a list of evoked over different subjects [13]. Evoked objects typically store an EEG or MEG signal that has been averaged over multiple epochs, which is a common technique for estimating stimulus-evoked activity. In Fig. 10, The data in an Evoked object are stored in an array of shapes (n_channels, n_times) [14]. These evoked objects are further used to create the head topology map (see Fig. 3) wherein the objects are classified as EEG images for different frequency spectrums, also called frequency binning. The FFT amplitudes were grouped into theta (4-8Hz), alpha(8-12Hz), and beta(12-40Hz) ranges, giving 3 scalar values for each probe per frame.

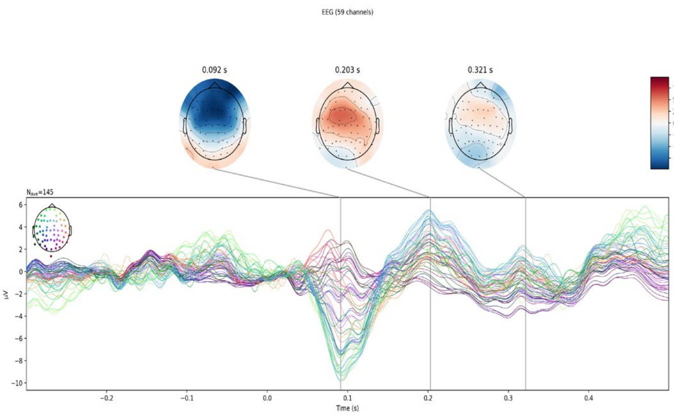

Fig. 10. Extracting evoked objects

- **Topography plot of head:** The processed data was converted into RGB format and plotted using matplotlib in RGB format for the 3 Classifiers. The Color Map is grouped as follows, seen in Fig. 11.
  - **Red:** Theta (4-8Hz)
  - **Green:** Alpha (8-12Hz)
  - **Blue:** Beta (12-40Hz)

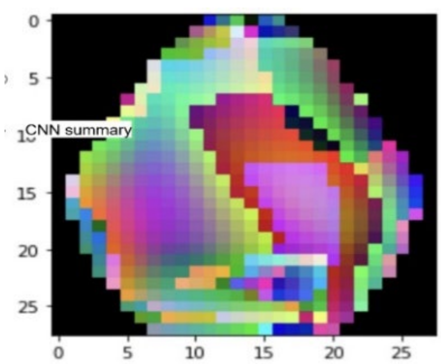

Fig. 11. RGB colour coded formatting of evoked topological map

B. Inducing sleep with Dichotic binaural beats

The data are in the form of csv files with raw waveform signals from 14 probes around the scalp. The sampling rate is 128 Hz, which allows for frequency analysis up to ~ 60 Hz. Each of the 8 subjects participated in two 1-minute sessions. Therefore, the total number of data points are 14x128x60x8x2 = 1,720,320.

The end goal is to develop a classifier that is capable of accurately classifying RGB snippets of EEG session data from the processed data visualization. Since this is a binary classification problem with balanced classes, the minimum baseline for accuracy is 0.5. Full success would mean having an accuracy of at least 70% (although this number is arbitrary). This format makes for ideal inputs into a standard convolutional neural network. A rectified linear unit (ReLU) is used as the activation function. Finally, a fully connected layer with a SoftMax activation function is used to compute the probability of each class. Weights were learned using the Adam optimizer. Hence, we used above mentioned pCNN sequential model to achieve the highest possible accuracy.

- **CNN Summary and model Accuracy:** The results for the CNN performed are as follows, shown in Fig. 12.
  - Total params: 64,256
  - Trainable params: 64,256
  - Non-trainable params: 0

TABLE 2. CNN STRUCTURE SUMMARY

Model: Sequential		
Layer	***Output Shape***	***Parameters #***
Conv2D	(None, 28, 28, 32)	896
Activation	(None, 28, 28, 32)	0
Conv2D_1	(None, 26, 26, 32)	9248
Activation_1	(None, 26, 26, 32)	0
MaxPooling2D	(None, 13, 13, 32)	0
Flatten	(None, 5408)	0
Dense	(None, 10)	54090
Activation_2	(None, 10)	0
Dense_1	(None, 2)	22
Activation_3	(None, 2)	0

The model test accuracy is 80%.

```
print('Test loss:', test_eval[0])
print('Test accuracy:', test_eval[1])
✓ 0.1s
Test loss: 0.5619903802871704
Test accuracy: 0.8024691343307495
```

Fig. 12. Accuracy Results

- **Generate binaural sound with a base frequency of 420 Hz:** The base frequency was chosen as 420 Hz because these frequency bands are reported to impact positive effects on our brains [15]. The generation of the sound is shown in Fig. 13.

```
# set some variables ...
left_freq = (420+sum1)
right_freq = (420+sum2)
#left_freq = 20
#right_freq = 12.17
# data size, file size will be about 2 times that
# duration is about 4 seconds for a data_size of 40000
data_size = 100000

# write the synthetic wave file to ...
fname = "binaural_cosmos_awaken_%s_%s.wav" % (left_freq, right_freq)

make_soundfile(left_freq, right_freq, data_size, fname)

#################### play the audio signal ############################

fs_rate, signal = wavfile.read(fname)


# Start playback
#play_buffer(audio_data, num_channels, bytes_per_sample, sample_rate)
play_obj = sa.play_buffer(signal, 2, 2, fs_rate)

# Wait for playback to finish before exiting
play_obj.wait_done()
plot_audio_wave (fs_rate,signal)
```

Fig. 13. Binaural Tone Generation

VI. CONCLUSION

Brainwave entrainment is a rather vast area of research and requires equally large-scale project development. We have presented a basic prototype tool to test the success of brainwave activity classifications and entrainment via binaural tunes in this paper. Our delta activity-inducing tool covers the following EEG data analyses and performs the auditory entrainment behavior: **1.** EEG segmentation tool helped in the extraction of frequency bands of brain regions' EEG data, **2.** BDS formatting tool was used to convert EEG to BDS format and enables visualization of EEG signals, **3.** EEG signal classification tool was used to classify the EEG data into different signal bands- alpha, beta, and theta, and **4.** Delta activity promotion was tested using dichotic binaural beats at a base frequency of 420 Hz.

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