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Thought identification through visual stimuli presentation from a commercially available EEG device

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***Abstract* - Thought identification has been the ultimate goal of brain-computer interface systems. However, due to the complex nature of brain signals, classification is difficult. But recent developments in deep learning have made the classification of multivariate time series data relatively easy. Studies have been carried out in the recent past to classify thoughts based on signals from medical-grade EEG devices. This study explores the possibility of thought identification using a commercially available EEG device using deep learning techniques. The crucial part of any EEG experiment is contamination-free data collection. Keeping the subject's mind concentrated only in the decided state is important, yet challenging. To address this issue, we have developed a graphical user interface (GUI) based program that allows stimulus controlling and data recording. With the use of the low-cost commercially available EEG device, accuracies up to 89% were achieved for the classification of high contrast signals. However, tests on complex thought identification did not produce statistically significant results over the chance accuracy.**

Keywords - brain-computer-interface, classification, EEG, signal processing

I. INTRODUCTION

Electroencephalography (EEG) is the method of observing the electrical activity of the brain by the electrodes placed on the scalp. EEG is one of the most used brain imaging techniques in the medical field. Other than medical uses, EEG devices have found their way into the research field of Brain-Computer Interfaces (BCI). The ultimate goal of a BCI system is extracting thoughts directly from the brain. Studying this area often requires expensive research-grade EEG devices. But there are many advantages of using a low-cost device, mainly their accessibility. In recent years, there has been an increase in the availability of low-cost EEG devices in the consumer market. This study was conducted using one of these low-cost devices, the Emotiv Insight 5–channel EEG headset.

This study explores the feasibility of identifying thoughts by captured brainwave signals using a commercially available low-cost EEG headset. The focus of this study was to visually stimulate a subject's brain with stimuli of a limited number of stimulus classes and later identify the stimulus class from the recorded EEG data.
This is not a simple task since EEG signals represent the electric potential changes on the scalp that correspond to the electrical activities in the brain that are received from the electrodes and are all higgledy-piggledy. Differentiating two EEG signals of two separate thoughts is quite difficult with traditional methods. Therefore, the proposed method employs Deep Learning techniques.
Proposed EEG experiments were all highly time-sensitive. The recording of the data needed to be done simultaneously with the presentation of the stimulus. This would not be possible without the use of an automated system to control the stimulus and capture data simultaneously. Therefore, a major contribution of this research is the development of the GUI. It allows seamless data capturing, managing, and saving. This makes the data-gathering stage effective and influences the overall outcome of the experiment.

If the classification is proven to be possible using a low-cost EEG headset, this technique can be extended to develop better low-cost BCIs. Another use case of this technique is that it can be used as the base for a communication platform that will assist differently-abled people with communication. This technique can also be used in game development to allow players to control certain actions based on what goes on in the player's mind. This will lead to mind-controlled gaming.

II. LITERATURE REVIEW

The Emotiv Insight EEG headset used in this study is a relatively low-cost commercially available device. Most of the published studies using this device have used the provided software by the MANUFACTURER. The study done by Stoelinga [1] has utilized raw EEG data from the headset. When using the manufacturer's software, it uses all the inbuilt sensors (Accelerometer, Gyroscope, Magnetometer, etc.) of the EEG headset to produce the output. Even though the use of the manufacturer's software could produce better results, it may not solely be based on EEG signals, since the signals picked up by the extra sensors could influence the outcome.

Experiments performed with EEG headsets vary widely from medical diagnosis [2]–[4], emotion recognition [5], to BCI applications [6], [7] all of which use some form of learning-based analysis for classification. All these studies used high contrast EEG data. Medical EEG data like Seizures [2], Epilepsy [3], or brain-dead and coma states [4] produce highly contrasting data. This is similar for emotion [5] and Motor-Imagery data [1], [6], [7]. Motor-Imagery is imagining moving a body part (e.g. raising an arm) without acting. Even though processing EEG signals to retrieve information is not new, classifying two distinct thoughts with low contrast data is still challenging.

Extracting thoughts from EEG data has been the primary goal of the BCI research. To that end, similar studies have been conducted where one or multiple subjects were shown images of multiple classes and later tried to identify the thought of the class from the EEG data. In 2017 one study [8] proposed an automated visual classification. But a study published in 2020 [9], questioned the stimulus presentation method of the said previous study while proposing a randomized stimulus presentation. Both studies used raw data for the classification by Deep Learning techniques. Another study published in 2020 [10] used an Evoked Potential extraction on the EEG signal and achieved a higher classification accuracy. However, these studies have used EEG devices with higher electrode counts and higher sampling rates than the EMOTIV Insight headset used in this study.

Practical use of thought identification can be identified as a yes-no classification because the most fundamental linguistic response of human speech is answering a "yes-no" question. An EEG-based system that understands a simple yes-no thought of a subject is extremely useful for people who have speech and muscle control disabilities like Amyotrophic Lateral Sclerosis (ALS) patients. A study published in 2019 [11] used EEG data gathered from multiple subjects responding to self-referential questions on a screen. There were no visual stimuli attached with the questions. The questions were uniquely generated for each subject based on a questionnaire given to them. Similar to yes-no detection, lie detection was another area explored with EEG devices [12], [13].

BCI research study requirements are usually time-sensitive. Most of the studies which were focused on BCI research applications used their software tool for data collection. The tools were extremely specific for those studies and most often cannot be used by others. There were some studies [14] that designed EEG stimulus presentation software to use in other studies. But most of them either did not work with the used EEG headset of this study or did not include features critical for the experiments like having a darker background.

Through this literature review, it was made aware that there was not much research conducted in the area of differentiating the thoughts yes and no with EEG data. And it was made clear that the most efficient way of analyzing complex EEG data is by using a learning-based technique. It was also identified the need for a software tool of some kind to efficiently collect and manage the EEG data.

III. METHODOLOGY

The methodology of the study can be summarized as the flow diagram shown in Fig.1. To successfully execute the proposed procedure, the following factors were considered.

- Simultaneous image presentation while recording the broadcasted EEG signals.
- Tag the EEG stream with the class of the image shown on the screen.
- Having a fixed sample length for each stimulus
- A distraction-free data collection

When the subject is looking at an image for a set period, the class of the shown image needs to be saved (tagged) with the recorded EEG stream. If the EEG stream is to be manually tagged by the subject who is wearing the EEG headset, the EEG data will get contaminated with the "thought of tagging".

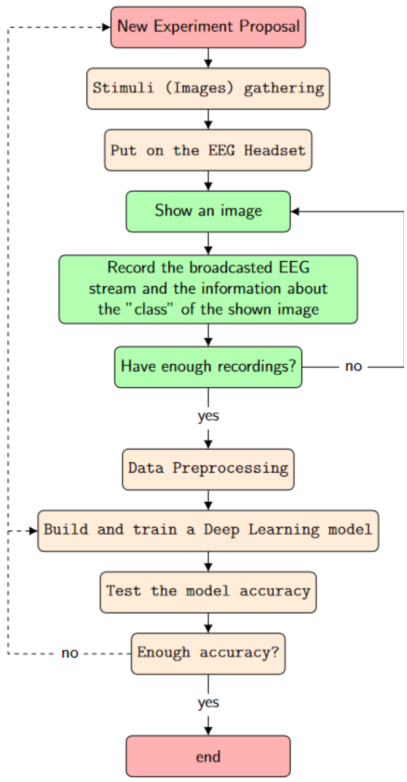

Fig. 1. Experiment procedure

Further, even if a third party was assigned for tagging with a mechanism similar to pressing a button every time the stimulus class changes, it will introduce human error into the experiment. A person performing the tagging will always introduce a random delay (error) between the time of stimulus change and the time of pressing the button.

Considering all these conditions, to make data collection consistent throughout the study, a program was developed to automate the proposed procedure.

A. *Graphical User Interface (GUI)*

The Graphical User Interface (GUI) was developed from scratch using the Python programming language. The main purpose of this GUI was to automate the tasks of capturing, saving, and managing the EEG data. Additionally, when building the GUI, special attention was given to the overall theme. A darker color pallet and low contrast fonts were used to keep the attention of the subject always on the area where the stimulus would be displayed on the screen when the software is used to gather data from stimuli. Since staring at a bright screen easily strains human eyes, using a darker background was found to be crucial for long recording sessions. Fig. 2 shows the main user interface of the GUI.

Here, the user can set the parameters of the experiment. Fig.3 shows what parameters are available to the user. Descriptions of the user-controllable parameters are as follows.

1) Interval – The period between two images.

2) Count – Number of images per one recording.

3) Subject Name – Name of the participant.
4) Project Name – Selection list of available image sets.
5) Start Recording – Button to click on to start the recording process

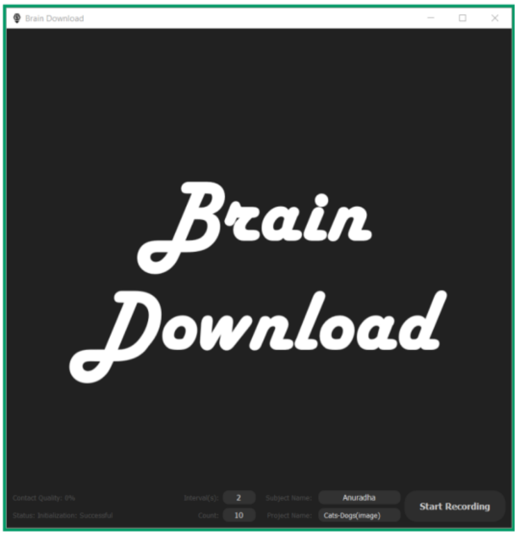

Fig. 2. Main interface

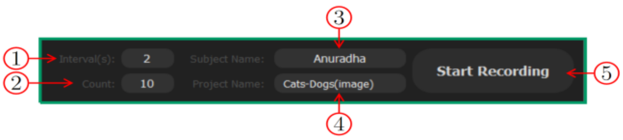

Fig. 3. User control parameters

B. *GUI program flow*

During the *image sequencing* process, which is in green color on Fig. 4, the GUI simultaneously records the EEG stream with some additional information.

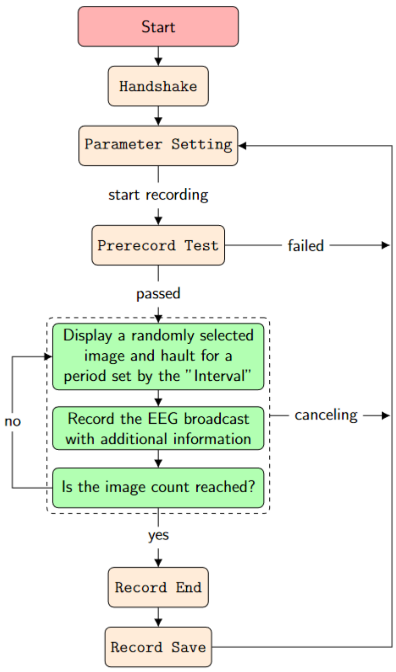

Fig. 4. Program flow of the GUI

A saved EEG recording contains data from 9 different variables,

- 5 – EEG channel (AF3, AF4, T7, T8, Pz)
- COUNT – A data packet counter.
- Contact Quality – Contact quality of the electrodes.
- TICK – Track the stimulus change.
- MARKERS – Track the class of the stimulus.

Data variables except TICK and MARKERS are directly captured from the broadcasted EEG stream. TICK and MARKER variables were added by the GUI to track the changes of the stimuli.

The TICK variable has two states, 0 and 1. Every time the GUI changes the image, the TICK changes its state. A record will contain several seconds long continuous stream of 5 EEG channel data. But to analyze the data, the stream needed to be separated into chunks depending on the stimulus shown period (interval). Since the variable TICK changes with every new image, it is used to identify the positions where the data stream needs to be split.

The MARKERS variable encapsulates the class of the image. When an image folder is selected, the GUI scans all the image files in the folder and identifies their unique classes. For example, for a folder that contains images of 4 types of vehicles [car, bus, train, bicycle], first, the program arranges the unique class names in the ascending order as [bicycle, bus, car, train] and assigns four index values starting from 0 as [0, 1, 2, 3]. When an image is shown on the screen, the value assigned to the image gets recorded as the MARKERS value throughout that image presentation period. For example, if an image of a car is shown on the computer screen, the value 2 will get recorded as the MARKERS until the next image is selected. After the stream is separated into chunks at the 'preprocessing' stage, they get labeled according to the values of the MARKERS variable.

When the GUI has shown a number of images specified by the researcher, the recording stops and the program saves the record in the computer hard disk as a .csv file.

Since the recording stage of this study stretched for several months, to save the records in a meaningful manner, the program uses the following naming convention when saving the recorded data.

[projectName][interval]sx[count][DATE]-[TIME].csv

The bracketed variables get replaced by the parameters set by the user. From this naming convention, all the necessary information about the record can be easily identified from the record name.

During communication, other than words humans often use body language and head movements to convey their inner thought to the other person. Used EEG headset can capture head movement data using the inbuilt sensors of accelerometer, gyroscope, and a magnetometer. When presented with a yes-no question, people unconsciously nod their head for the answer yes and move their head side-to-side for the answer no. Hence, head movements might give an extra edge with thought identification. Since the focus of the study is thought identification with EEG signals, the head movement data was not associated with the analysis.

C. *Sample record*

Each exported EEG record from the GUI contains EEG signals of watching several stimulus presentations. Fig. 5 shows a sample record of a subject watching 20 consecutive image presentations with 2-second image intervals.

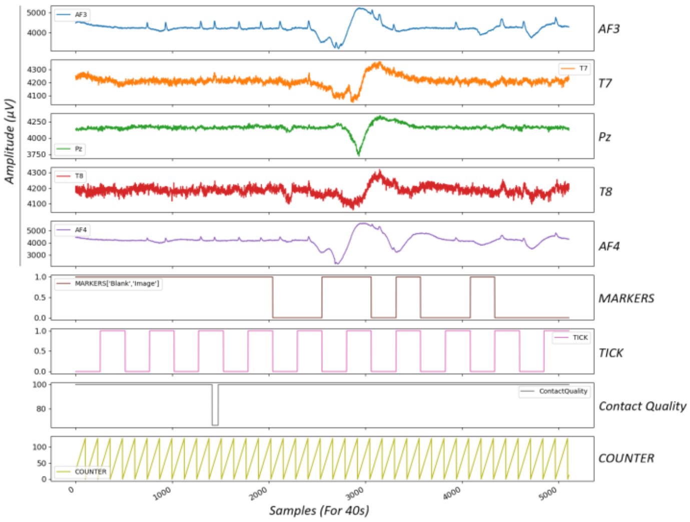

Fig. 5. Exported record from the GUI

D. *Stimulus presentation methods*

To visually stimulate the subject's brain, various methods were identified, in which the images of multiple classes can be presented.

One method of stimulus presentation is separating the whole image-set into subsets based on their class as suggested in [8] and continuously displaying images of one subset at a time, as shown in Fig.6. In Fig. 6, a two-class image set is separated into two sections (shown in two different colors for simplicity) and images of one set are displayed first before the images of the other set are displayed.

However, with this method, since all the images of a class are shown continuously, captured brain wave patterns are temporally correlated. This means EEG signals of each class will contain the patterns of the long-term mental state of the subject. For example, assume in this case (Fig. 6) the subject is looking at images of Class B first and then Class A during the experiment. In the beginning, the subject might be in an excited mood, and most of the EEG signals of Class B will capture that exited brain pattern. But at the end of the experiment, the subject might get bored, and those brain patterns will get captured in the EEG signals of Class A. When classifying these brainwaves, rather than detecting the thought of the presented stimuli, the brainwaves of excitement and boredom will get precedence.

Instead of separating the stimuli into individual classes and showing all images of one class before proceeding to the other classes, the image-set can be separated into smaller batches based on their class as shown in Fig. 7 and alternatively show each batch from separate classes. This method reduces the temporal correlation but not completely. If the length of the batch is too long, the error remains.

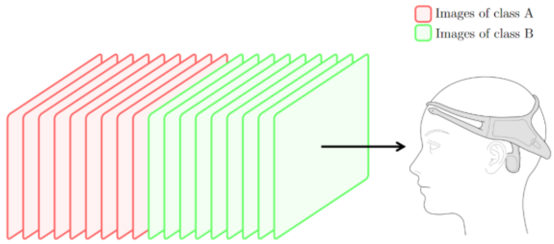

Fig. 6. Image-set was separate into classes

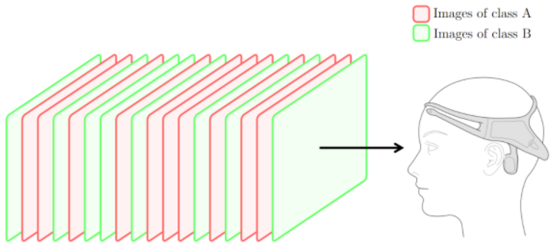

Fig. 7. Image-set was separated into multiple batches.

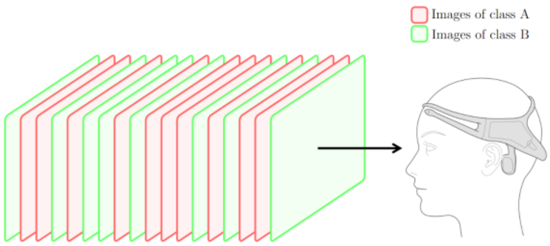

Fig. 8. The subject was presented with randomly selected images from the image-set

To eliminate the errors discussed above, it requires a randomized stimulus presentation [9] as shown in Fig. 8. If it is not randomized, and the presentation is similar to Fig. 7, the subject's brain will recognize the stimuli presentation pattern and will know what to expect in the next image. This can also be eliminated by using a randomized stimulus presentation. Hence, all conducted experiments in this study used a randomized stimulus presentation method.

E. *Signal filtering and dataset conversions*

At the preprocessing stage, the recorded long EEG signals were separated into smaller chunks of the subject watching one stimulus using the TICK variable. The MARKERS variable was used to label the separated chunks.

After the basic preprocessing, the obtained raw dataset was converted into 3 other forms to find out whether the classification accuracy of the deep learning model can be improved.

- The raw dataset was converted into the frequency domain using the Fast Fourier Transformation (FFT).
- Filtered the low-frequency blinking artifacts by adding a high pass filter at 12 Hz and filtered the 50 Hz electromagnetic interference by adding a notch filter.

- Using the Short-Time Fourier Transformation (STFT) each chunk in the raw dataset was converted into a stacked spectrogram.

To generate a stacked spectrogram, first, a chunk was selected from the raw dataset. Then each of the 5 EEG signals was converted into separate spectrograms using STFT (see Fig. 9). Then all the generated spectrograms were stacked on top of each other to generate a diagram similar to what is shown in Fig. 10.

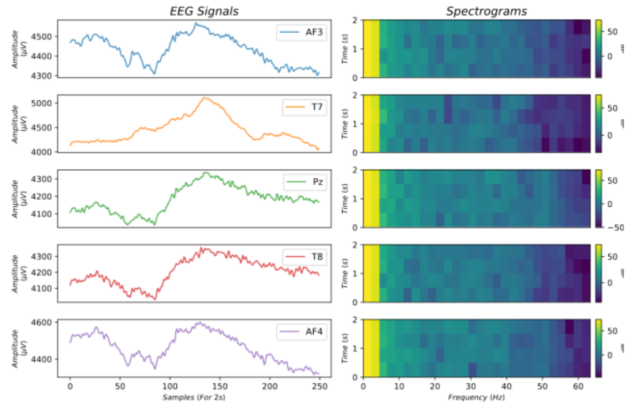

Fig. 9. 5 EEG signals converted separately into spectrograms

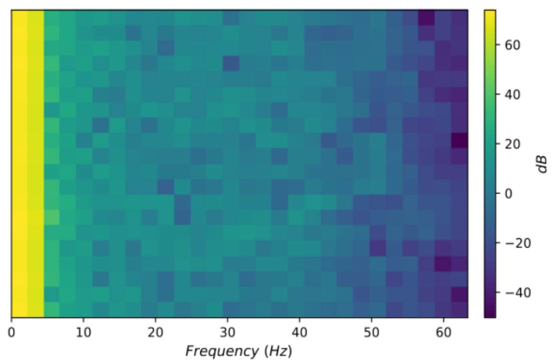

Fig. 10. Stacked spectrogram

F. *Conducted experiments*

To assess the feasibility of thought identification from the used low-cost EEG device, four experiments were conducted where the participant's brain was visually stimulated by a presentation of image sequences. Only one subject was used for all the experiments conducted.

- *Experiment 1* – Simulated thinking "something" and "nothing" on the subject's brain by randomly presenting images and blank screens to the subject.
- *Experiment 2* – Showed left and right directed arrows on the left and right edges of the screen respectively and the subject was instructed to directly look at them without moving the head. Since the image sequence is randomized, a reference mark was presented at the center of the screen after each arrow image.
- *Experiment 3* – Simultaneously displayed a yes-no question about the presented image and instructed the subject to think about the answer.
- *Experiment 4* – Showed images of cats and dogs, and the subject was instructed to identify the class of the image as a "cat" or a "dog".

IV. RESULTS

In this study, we employed 2 deep learning models for the classification of the recorded EEG data. A one-dimensional Convolutional Neural Network (1D-CNN) was used for the classification of the multivariate time series data. The classification of the stacked spectrograms was done using a two-dimensional Convolutional Neural Network (2D-CNN) [15].

A. *Classification results of the three experiments*

TABLE II. CLASSIFICATION RESULTS

Experiment	**Classes**	**Dataset**	**Classification accuracy (%)**	
			1D-CNN	**2D-CNN**
Thinking "something" and "nothing"	Image, Blank	Raw	80	-
		FFT	79	-
		Filtered	80	-
		Spectrograms	-	74
Left-Right arrows	Center, Left, Right	Raw	68	-
		FFT	67	-
		Filtered	67	-
		Spectrograms	-	69
	Left, Right	Raw	89	-
		Filtered	91	-
Yes-No	Yes, No	Raw	45	-
		FFT	43	-
		Filtered	45	-
		Spectrograms	-	50
Cats-Dogs	Cat, Dog	Raw	52	-
		Spectrograms	-	54

Since experiment 2 presented a reference mark at the center of the screen, it contained EEG recordings of 3 separate classes of Center, Left, and Right. For three classes, the highest classification accuracy of 69% was achieved by the 2D-CNN model. For the classification of EEG signals of looking only Left and Right, the 1D-CNN reached an 89% accuracy.

It is important to notice that using spectrograms with a 2D-CNN model, there was no statistically significant improvement. All the results are fairly similar between both models. Also, the additional conversions of Fourier transformation and filtering done on the data did not increase the accuracies of the models.

B. *Channel contributions*

Individual datasets contain 5 separate EEG signals. Table I shows results of experiment 1 when all 5 EEG channels were concerned and maximum classification accuracy of 80% for the 1D-CNN model was achieved for both the raw and filtered datasets. Table II shows the classification results of several EEG channel combinations of experiment 1. By selecting multiple combinations of EEG channels, the study tried to identify a channel or combination which contributes the most to the final accuracy. Only models that performed above the random chance accuracy of 50% are listed.

TABLE III. CLASSIFICATION RESULTS OF SELECTING MULTIPLE CHANNEL COMBINATIONS

Channel combinations	**1D-CNN classification accuracy of experiment 1 (%)**	
	Raw	**Filtered**
AF3, T7, Pz, T8, AF4	80	80
AF3, Pz	80	80
AF3, Pz, T8	80	78
AF4, Pz, T8	80	79
AF4, Pz	78	77
AF3	73	70
AF3, AF4	68	68
Pz	64	64
T8	54	56
T7	51	51

These results further clarify the fact that filtering done on the raw data did not affect the final accuracy of the model.

V. CONCLUSION

The automated data collection and tagging method implemented using the GUI were found to be crucial for acquiring contamination-free EEG samples. Since the GUI allowed effortless sample management, in a relatively short period we were able to gather EEG samples from multiple experiments.

Even though several studies have been published that converted the raw data into other formats such as spectrographs [4], [5] and scalograms [3], [6], [7], the analysis of this study suggests using only raw data for the classification is sufficient for the data gathered with Emotiv Insight 5–channel EEG headset, which is a low-cost EEG device.

Even though the classification of experiments 1 and 2 reached higher accuracies this might not be solely based on EEG signals. The coneo-retinal potential [16] might have played a major role in this. This is also confirmed by the results presented in Table II. When the frontal lobe channels of AF3 and AF4 are not selected, the accuracy drops considerably. Therefore, for complex thought identification tasks such as yes-no answer identification and distinct thought classification (thinking “cat” versus “dog”), we recommend using a device with a higher electrode count.

VI. LIMITATIONS

Since the GUI is built around one EEG headset (Emotiv-Insight) in mind, it cannot be used with EEG headsets of other manufacturers. But with minor changes, the GUI can be made to work with other models of EEG devices of the same manufacturer (EMOTIV). However, the concept can be applied to any EEG device.

VII. RECOMMENDATION

All the experiments conducted for binary classification had a balanced stimuli presentation. Future research can be conducted to see the effects of unbalancing the image-set on the final accuracy. Also, for the analysis of this study the whole EEG signals of watching a 2-second stimulus was used. A study can be conducted to see the effect on the accuracy of the model when a shorter length is selected from the EEG signals.

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