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# Understanding Responses to Stimuli (Emotions) using Brainwaves in Order to Regulate them and Utilize the Data to Develop Intelligent Machines

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***Abstract: This is a review paper based on research papers written by various authors. The topics and/or themes discussed in this review paper belong to a currently very active field of research, known as the ARTIFICIAL INTELLIGENCE. Most of the major tech companies are focusing in this arena, and trying to develop even more intelligent machines. Ages ago, the abacus was invented which assisted in mathematical calculation. Further, the calculators were invented which could solve massive amounts of calculations in a very short span of time. Then the digitization happened. And the computers were invented, which not only helped in computing math, but assisted in a lot of things as well. And people, since a very long time, have been trying to improve the machines. Their responses, computation rate and capabilities. And thus, work has been continuously carried out, since a very long time, to construct intelligent machines. Allan Turing is said, to have constructed the first intelligent machine during the world war. And since then, it has been an area of constant and rigorous research to make the machines more intelligent, so that they can ease our work as well as daily routine. This review discusses five research papers, based on Neural Networks, Brain Computer Interface, Brainwaves and Artificial Intelligence. This review discusses the methods used by the authors of the research papers, and how those methods might or might not help, in an ongoing research which discusses the possibilities of integrating emotions of a person into a machine, and accordingly the performance of the machine on its own, without human interference in certain situations and cases. This review discusses the pros and cons of the research papers, and the improvements which are either available already, or which can be implemented, to obtain better results and ease as well as fasten the advancements in the field.***
***Keywords: EEG, Neural Networks, AI, Neurosky***

## I. INTRODUCTION

Due to extension of machines' ability, people are beginning to have more opportunities to work with machines familiarly. Brain Computer Interaction (BCI) [19] is the field which uses EEG and other brain function measurements for this kind of human machine interaction. The study to recognize human emotions using EEG data is called EEG-based Emotion Recognition or EEG-ER. The EEG-ER model which is provided raw EEG data and outputs equivalent emotional valence has the potential to become one of the powerful tools in neuromarketing as well as advanced AI development in the near future. Though scalp EEG has advantage of high temporal resolution, non-invasive data gathering, and simplicity in recordings, it includes a lot of noises and lacks spatial resolution. To make EEG-ER models available, it is necessary to analyze massive data in order to compensate for defect of EEG and to discover the properties characterizing a certain mental state. But recent developments in the semiconductor industry has led to development of handy spatial devices which record brainwaves with minimal noise, for example NEUROSKY MINDWAVE. Convolutional Neural Networks(CNNs) have few parameters because of its local connections. In addition, the convolutional layer is suitable for inputting raw data because it need not disband the structure of data. Actually, CNNs exhibit better results than those of DNNs consisting of fully-connected layers not only in image but also in speech [6].

This research and project is not trying to prove which method of EEG recognition is better in contrast to another, because it has already been discussed earlier and proven that as the technology advances and newer devices are made available, the latest devices possess high level EEG recording capabilities, with minimal noise. This research is trying to provide a method, which can relate the emotional valence and the response to external stimulus, like words and music and other factors which affect the mood of a person resulting in change in the brainwave frequency. Thus, this project records the brainwave activity of the subject in response to different external stimulus, thus creating a rich database. This database is then used to create the dictionary of the words and other factors used to record the subject's response to the stimulus. Further, that dictionary is given as input to the AI system which is currently being developed as a CHAT BOT. This method, provides a possible line of work which can not only be used in AI, but also in Neurological research and medical assistance.

## II. BRAINWAVES AND HOW THEY WORK

Human brain is made up of billions of brain cells known as neurons. These brain cells use synchronized electrical pulses to communicate with each other. The combination of electrical activity of the brain produce waves commonly known as brainwaves. These waves are detected and recorded by EEG equipment by placing a either a number of electrodes on the subject's scalp or by placing an EEG recording device on the scalp. The amplitude, frequency and phase of these waves depend on the location of the electrodes. For example, at the cranial surface, the amplitude ranges from 1 to 100µV at low frequencies while at the cerebrum, it can be 10 times stronger. The frequency bands are usually classified into five categories as follows [7]:

*A.* Delta (δ) waves 0.5-4 Hz
*B.* Theta (θ) waves 4-8 Hz
*C.* Alpha (α) waves 8-13 Hz
*D.* Beta (β) waves 13-22 Hz
*E.* Gamma (γ) waves 22-30 Hz and above.

Delta (δ) waves are usually low frequency and high amplitude brainwaves. These types of signals are usually observed during DEEP DREAMLESS SLEEP and extremely DEEPEST MEDITATION. When people remain in this state, they are completely unaware of the external environment. These are also dominant waves among infants, since a major portion of their day's cycle includes deep sleep. Theta (θ) waves are slightly high frequency and low amplitude than delta waves. Theta waves are usually associated with REDUCED CONSCIENCE, DROWSINESS OR LIGHT SLEEP. Alpha (α) waves are of around 10µV peak to peak amplitude and are a result of most STABLE AND BALANCED STATE. This is associated with physical and mental relaxation but a complete awareness of surrounding. Alpha waves help overall mind body coordination, calmness, alertness and learning, and is prominent during the states like, meditation, yoga etc [17].

Beta (β) waves are less than 20µV peak to peak and indicate HIGH STATE OF WAKEFULLNESS. When we remain highly alert, focused, or get agitated, tensed, afraid, perform calculations, we experience more beta waves. These waves are also associated with some mental disorders such as ANXIETY, INSOMNIA OR OCD etc. Gamma (γ) waves are the highest frequency brain waves and linked with HIGHLY DISORDERED BRAIN FUNCTION. For various reasons, which can either be internal as well as external, human mood and their related brain waves change. Mentally healthy people do a lot to regulate their brain waves or adjust their moods naturally (giving time to adjust) and unnaturally (forcing a distraction). Such, as meditation, listening to music, watching television, relaxation or deep breathing practice, yoga, praying etc. However, physically and mentally challenged people cannot do such for their mood adjustment [8]. Also, even if a person conceals the real emotional response to the different stimulus, the brainwaves help to recognize the actual emotions. Thus, brainwaves can actually be very helpful in understanding the responses of the brain to different stimulus.

## III. HISTORY OF WORK ON BRAINWAVES

Many works belonging to fields of EEG-ER aim at recognizing emotions which are done for long durations of time to achieve high accuracy. Although methodology of ERP (Event Related Potential) is famous in EEG analysis, ERP is not used in these works because of the duration. In EEG-ER, it has been general to use feature values derived from values in frequency domain (e.g. PSD) and classifiers performing machine learning (e.g. SVMs) so far. For example, Lu et al. proposed feature value DE (Differential Entropy) and demonstrated its availability by comparing accuracies of different features and combination of a SVM or KNN (k-nearest neighbor). In ER (Emotion Recognition), there are studies which aim at recognizing emotional valence or arousal from the viewpoint of a circumflex model of affect. There are methods to stimulate intended emotions including watching music videos, looking at images, and playing games [18].

## IV. LITERATURE REVIEW

The authors MIKU YANAGIMOTO, CHIKA SUGIMOTO of the paper [1] used EEG-ER models using CNN (Convolution Neural Networks) to verify the integrity and accuracy of some of the datasets he collected. The author refrained from using general pre-processes for instance, bandpass filtering or removing artefacts (noise). The values are provided to the CNN as raw input. Tests were performed frequently keeping in mind that the EEG signals are highly variable. All the raw data was provided to the CNN via the EEG signals [10].

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The author proposes further work and methods to enhance the accuracy of CNNs on the limited dataset experiments, wherein the author failed achieve a result due to lack of data. He suggests, that the model can use light EEG or mobile EEG which will simplify this method and capturing the EEG data, and can save a lot of time, along with superior feature evaluation. The author mentions, that he used 16 electrodes, which he says is not sufficient for light EEG. He suggests to develop a more robust model, to be able to gain more feature and exclude noise at a higher rate. The author also proposes that the emotional valence can also be interpreted from the filters of trained CNNs. Although the author was actually able to capture and detect emotions 20% more than the previous shallow models, the work need a lot of improvement. For instance, the CNN, was unable to detect or learn anything from the single subject dataset, due to lack of data. Hence, CNNs need to be constructed, which are able to learn even from a limited dataset. Further, the author uses 16 electrodes, according to the 10-20 rule of setting up the EEG electrodes on the head. These devices are capable of capturing and showing the EEG waves live, and possess much higher accuracy. Thus, this research provides a basic base to work further [20].

This research is about analyzing and feature extraction of different frequency bands belonging to the EEG channel. The authors of the paper, tested different frequency bands, EEG channel locations and feature extraction algorithms for finding the suitable ones in EEG based emotion recognition. The authors applied various feature extraction algorithms, for an instance, the mRMR was used for feature selection and SVM was used to carry out the classification.

The authors PASCAL ACKERMANN, CHRISTIAN, SABINA, JO of paper [2], discussed about the importance of the gamma wave features and EEG location corresponding to the pre-frontal and left temporal lobe for EEG emotion classification. And they were successful in cross verifying the obtained data from the findings in neurosciences. They propose to use Random Forests for EEG emotion recognition rather than SVM (Support Vector Machine), as they found evidence that RF works much simpler and is more robust than SVM. The authors, plan to carry the research forward, and develop EEG based emotion recognition to automatically detect depression. Although the authors used standardized algorithms to sort and classify the features of the EEG collected data [21]. The authors did not process the data to perform any operation. There are existing devices which can provide and display the brainwaves live, and the peak values of wave can be cross verified from the current values of the waves in order to understand the emotional valence of the patient. This paper, talks about finding the mood and extracting its features. This, research does provide a great deal of information about extracting features and corresponding frequencies of the brainwaves [11].

The authors ALAMGIR HOSSAN, A.M. CHOWDHURY of paper [3], researched on an approach to adjust the mood of various subjects who were physically or mentally challenged, by music. They successfully performed the research and the feasibility as well as the effectiveness of the approach were verified. They suggest, not only music, but any sort of entertainment material, can be used as a library in carrying out the research.

The research was meant to be for real time, EEG analysis, but due to monetary constraints the authors were unable to buy a real-time EEG monitoring system, and hence could not perform the research in real time. The research was performed using offline data which has been collected earlier. The authors suggest that their system can be used, not only in medical establishments but also in home applications for the aforementioned patients [16].

The authors suggest that this system can further be extended, for automatic mood regulation in real time, for the patients. The authors covered very few frequency of the waves, covering a limited amount of brainwave data, which can pose a problem in advance research [12].

The authors, were unable to obtain a real-time EEG system, and the whole research was conducted using offline data, which might be a problem, because real-time data and offline data may vary to a percentage more than expected. But according to the 10-20 system, the electrodes must be placed all along the skull, with a 10% and 20% distance, covering the Frontal, Central and Perinatal parts of the brain, so as to obtain and detect all or maximum number of waves that are being emitted. The major problem that might arise, if we consider very less part of the brain, is the effect of change in one wave, inflicting a change in the peak of another wave. Thus, considering a higher range of frequencies is very important for proper functioning of the system. But, the algorithms provided and suggested by the authors are feasible and does hold good even for real-time based EEG recognition systems. Since, in real-time EEG recognition systems the data is obtained continuously and thus, it can be easily captured and analyzed for any further function.

The authors TOMAS, PETER, ROBERT, JAKUB, MARIA of paper [4] carried out a comparative research on emotion detection using currently existing Facial Recognition technology, to that of EEG based emotion recognition. However, the authors were only able to achieve 58% accuracy for seven classes of waves, which imply six emotions including the neutral state. Thus, there can still be a lot of improvement in the work. But the results were achieved using a low-end affordable EEG-ER device, which suggests that, if we use an advanced device, which can capture EEG more precisely, we might be able to obtain higher accuracy rate [9].

Yet, the results obtained by the authors of this paper, are far more accurate and feasible than any other work prior to this paper. Since, prior to this method, facial expressions were used to detect and recognize emotions in humans, which had only 19% accuracy. Thus, this work proves that using EEG as an emotional recognition valence, have a huge potential.

The authors of this paper used a low-end EEG acquisition device, whereas if we use currently available high-end devices, we might get highly accurate data from the subject. Also, considering multiple subjects might prove to be useful as it is always beneficial to use multiple subjects.

## V. METHODS TO READ/RECOGNIZE EEG

EEG-based Thought Recognition EEG is recorded using EEG recognition and recording device available from NEUROSKY LABORATORIES, known as the NEUROSKY MINDWAVE MOBILE. This device is placed on the scalp, and is adjustable to head size. The device runs on regular batteries. It does not follow the usual 10-20 method. The two electrodes are placed on either side of the scalp, to measure the maximum amount of brainwave activity. Another electrode is placed on the earlobe. The device captures brainwaves and send it to the systems, in real time using Bluetooth. The change in the brainwave activity can be detected instantly at real time, using the device [21].

The subject will be required to be in a stable state of mind initially and be calm. Prior to the recording, a statement of the subject on various things the subject like or dislikes or is emotionally related to. Post setting up the device and the environment, the subject is asked various questions based on the statement recorded earlier. Also, the subject is shown various photographs and videos, as well as he is made to hear different kinds of music. The raw EEG data from the device, is recorded at real time. And changes are marked, whenever the signals show high amount of upsurge or downfall [13].

Multiple subjects are considered and their responses are recorded. After recording the response, the responses are tallied and the common emotional stimuli are sorted out. These values and their respective frequencies are fed to the system (AI). The dictionary is also integrated within the AI. Thus, during conversation or interaction of user with the chat bot, on certain combination of words, or on a certain audio/video stimuli, the system will respond accordingly. Also, an automated AI system can be fed the subject response data, and in case of need, the AI can help the subject [14].

## VI. PROPOSED METHOD FOR STORING EEG DATA

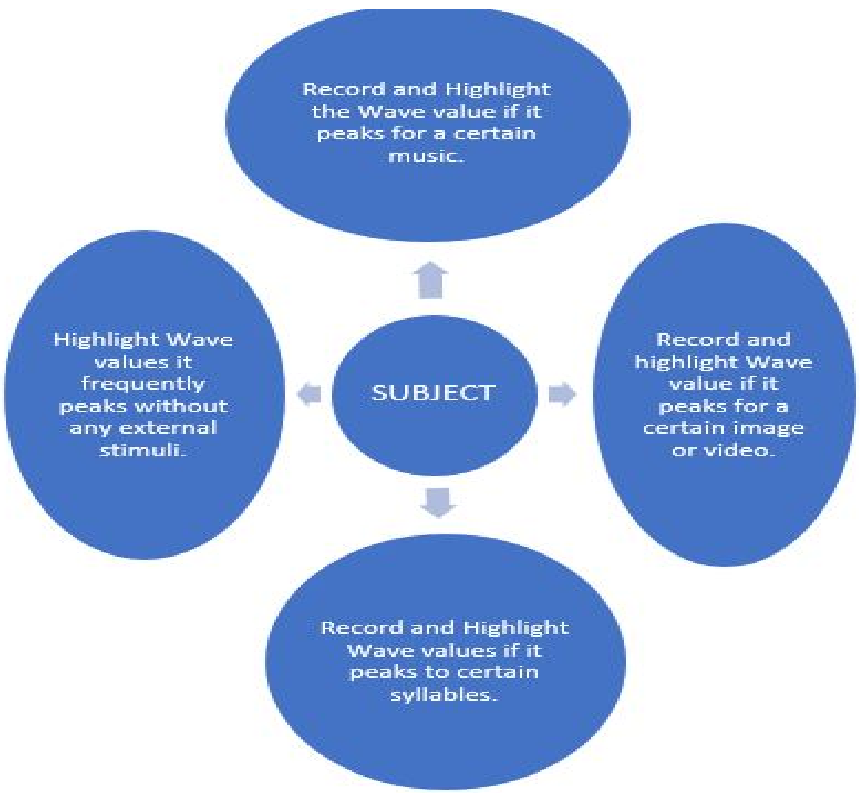


Fig. 1. Acquiring EEG data from subject

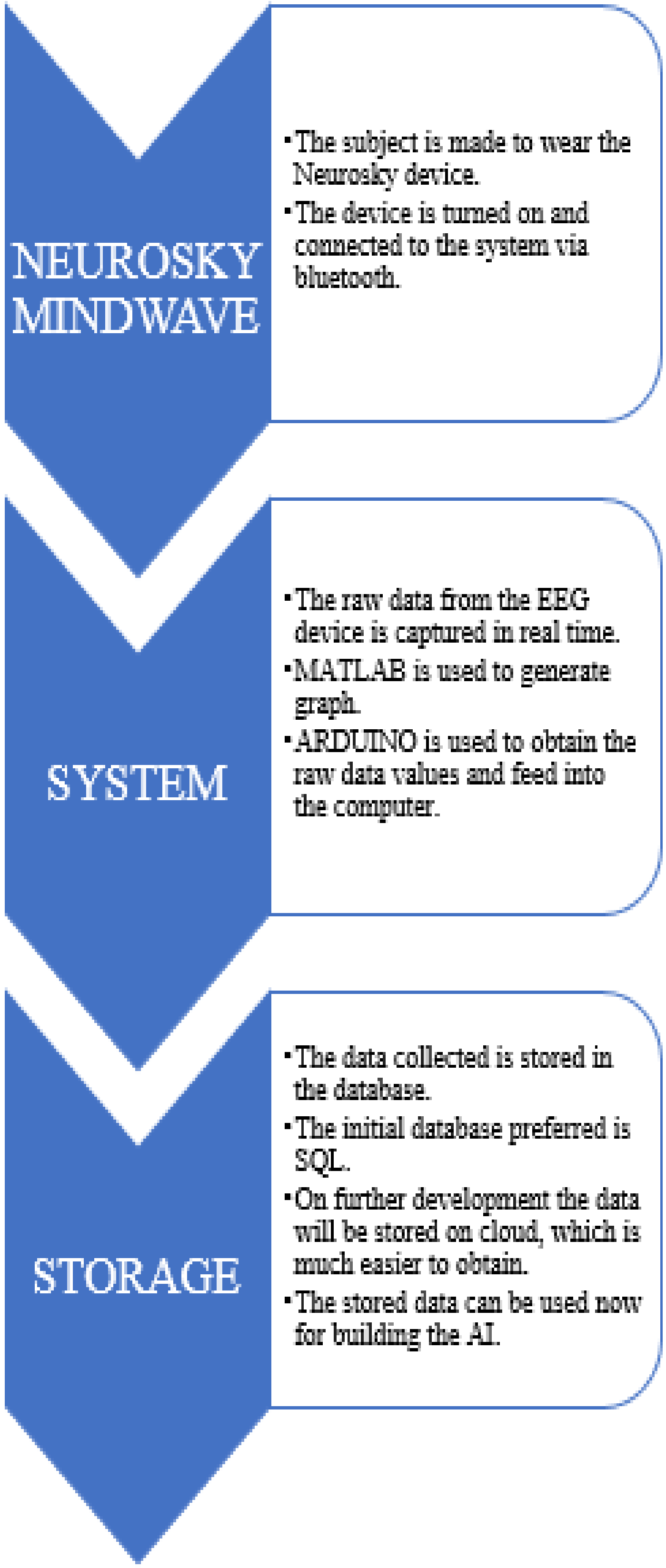


Fig. 2. Storing the EEG valence data

 

## VII. EEG SIGNAL ACQUISITION, PRE-PROCESSING AND BUFFERING

EEG data could be collected in real time from subject's scalp by using different commercially available, cost-effective user-friendly portable Neuro-headset, such as Emotive, X-wave, Muse etc. NEUROSKY provides, highly accurate brainwave data. The recorded signals are transferred via Bluetooth. For removing artefacts resulted from surroundings such as power line noise, NEUROSKY uses covered electrodes. These primarily processed data could directly be interfaced by MATLAB in real time by calling a dynamically-linked library (dll) routine. However, it used to be difficult to continuously stream and process data in real time since it requires some time for acquiring data and computing those data. To overcome that, earlier people used buffering software. But nowadays the data transmission using NEUROSKY is much faster and reliable [15]. Thus, no buffering software is required while using NEUROSKY. Further, some MATLAB based efficient tools, such as EEGLAB, BCILAB, BCI2000, Open Vibe, BioSig etc. are widely used nowadays for these sorts of BCI applications. The dataset used must be collected from several subjects at different conditions for a number of short duration. The data can either be directly captured, or imported in MATLAB workspace and processed according to the algorithm discussed in next section, to translate these brainwave signals into command to control the audio tracks, the responses of the AI system, to develop emotion chart [22].

## VIII. ALGORITHM DEVELOPMENT

An algorithm to implement the proposed approach was developed as described in this section. Consider multiple subjects, whose brainwave raw data were collected using the NEUROSKY device. Since the loaded data was captured using a highly accurate and sensitive device, there's no need to use any method for noise reduction, and since the device already gives a differentiated brainwave chart, bifurcating the waves automatically, the need for spectral analysis using any kind of FFT algorithm is diminished. The frequency corresponding to the peak amplitude was found out using simple looping and logical commands to determine which brain wave band ($\delta$, $\theta$, $\alpha$, $\beta$, $\gamma$) was dominant [23]. MATLAB audio read command can be used to play music tracks from the music library using soundcard.

The subject can be subjected to different statements as well, and the peaks in the frequency of the wavelengths can be recorded for that [16]. MATLAB video codec can be used to show videos to the subject. Initially different music/video tracks under three main categories, namely, relaxation, soft and motivational music, can be selected regarding subject's taste and preferences. These tracks can be saved in wav format in the current MATLAB directory. The number of music/video tracks could be changed desirably. In the AI system, the AI will get all this in the form of raw data and store it in a database. Further, the subjects' reaction to different words are recorded and stored and the dictionary is created and given to the AI. The proposed algorithm is shown in the figure underneath [24]. For actual coding and constructing the application the following are being used: -

*A.* WINDOWS 64B OS
*B.* MATLAB 32B
*C.* VISUAL STUDIO 2015
*D.* SWI PROLOG

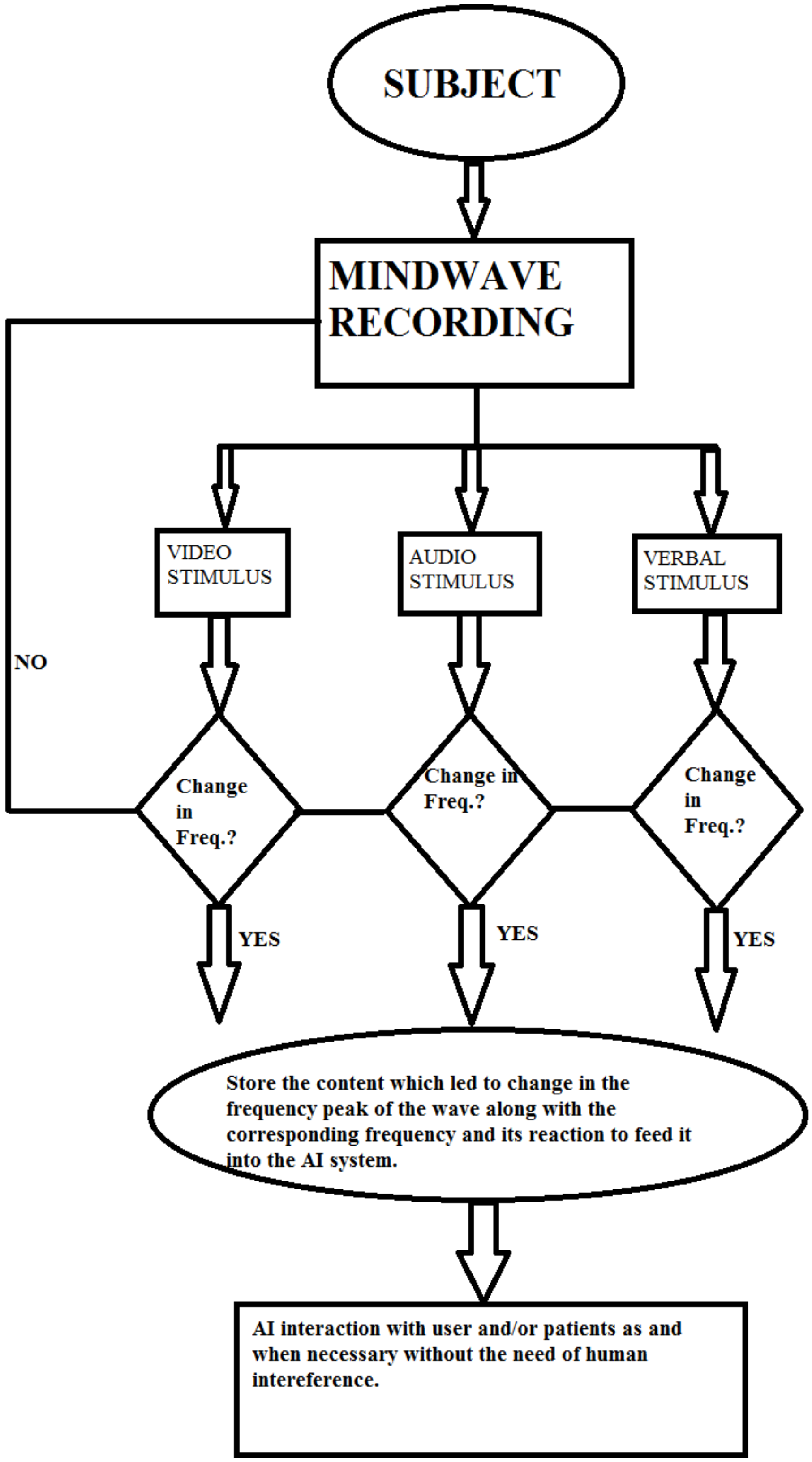


Fig. 3. Algorithm for the EEG model

## IX. CONCLUSION

The purpose of this research and the project is distributed amongst broad category of fields. On successful execution, we will be able to integrate natural and real responses to different stimuli for a machine. From the data collected, we can help patients with hyper brain activity calm down instantly by using the exact music. On giving input to the AI system, which has undergone the rigorous training using the values gathered from this experiment, the AI will soon be able to make decisions on its own, and provide optimal solutions in dire situations. This, procedure might also help in developing something everyone has been trying to do since a long time. To make a perfect music track for a person. The different frequencies and their responses can be analyzed for a matching frequency in the music notes, and hence after finding the notes, the AI system can generate its own music, which will be exactly matching to the frequency of the subject, thus instantly helping them. Such intelligent AI systems can also be integrated as IOT controller and control home appliances, helping to improve pace and quality of work [25].

Thus, this research focuses on how to extract brainwaves, record and store them, and give as input to the AI systems, which generate genuine responses and help increase the quality and quantity of digital services.

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