Detecting Brain Activity and Brain Disorders using Machine Learning Algorithms Applied on EEG Recordings

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Abstract:

Numerous studies have been implemented throughout the previous years to discover the activity of the brain through using different types of biomedical signals. In this study an experiment is implemented on EEG recordings in order to study the impact of external stimuli on the human brain. The experiment includes exposing 50 subjects to four various stimuli while recording EEG. At the first stage, a control experiment is done where EEG is recorded in the absence of any stimulation. In the second stage, stimuli are applied and EEG is recorded while watching two consecutive sections from nature and violence videos, and then listening to sections of classical music and then heavy music. The absolute and relative power spectral density of the different brain waves delta, theta, alpha and beta is measured. The signals from the two stages, with and without application of stimulation, are recorded. The recorded inputs of power spectral densities are computed. Then these recordings are analysed on neural network system with different training parameters (input layers, hidden layers, learning rate, training model and training epochs) using Python libraries to build the accurate model. In turn, later on, this model is used on new data input from new patient brain signals to predict the critical case by its current reaction taking the urgent and correct decision on spot. The results showed that the model was able to detect the relationship between the stimuli and the wave type with high accuracy.

Keywords: **Machine learning, Neural Networks, Electroencephalography, Tensor Flow and python, Keras Library ANOVA system**

1. INTRODUCTION

The brain may seem to be primarily one of the most interesting and complicated organs in the human body. This explains why the brain has been extensively studied and researched. Mainly since the beginning of the twentieth century, numerous research activities and advances have allowed scientists to discover more and more the "mysteries" of this organ [1]. Indeed, the discovery of the anatomy, functions and processes of the brain has been a long and continuous journey through history.

On another perspective, the brain responds differently to external stimulants. Therefore, due to several medical purposes, there is a crucial need to study the effects of different external stimulants, mainly auditory and visual, on the activity and functioning of the human brain. The ultimate objective of these studies is to help in detecting changes in the brain activity due to these stimulants. The result of these studies is to allow and open the way for more and more discoveries of the brain behavior as well as allowing the detection, description and characterization of different brain disorders.

After what has been stated, it can be said that studying the behavior of the brain represents a major concern for the worldwide medical society. Therefore, the study of brain activity is a necessary need for which many research activities are carried out with a view to finding methods to measure and represent brain activities.

One of the main complications of the brain is that it does not secrete visible material like other organs e.g. bladder, or pump blood like the heart. This means that even if you sliced it off and stared inside, that would not help you to know what's happening at all. The brain has its own mode of communication, i.e. it speaks the language of the 'electrical signal'. The study of the electrical activity of the brain has developed from simple galvanometer into the technology "Electroencephalography" (EEG) we use nowadays. EEG is a non-invasive, painless, and safe technique for studying the electrical activity of the brain. EEG measures and displays the electrical activity of the brain. It has the ability to detect wide variety of mental activities and brain disorders and diseases including autism, epilepsy, and dementia [2].

Different brain activities and disorder have been studied and discovered through the use of EEG recordings. Among these studies, various ones have been implemented to test the effect of stimulations on the brain via EEG. To mention

but a few, in [3] using the EEG technology, Geethanjali et al. (2012) studied the impact of three different types of music, Carnatic, Hard Rock and Jazz, on the brain function with and without performing mental task activity. In [4] Anilesh et al. (2013) examined the impact of music on the central nervous system by comparing the EEG of various subjects while listening to instrumental music to their EEG recorded in normal conditions. In the same context, Hurless et al. (2013) studied the effect of music genre and tempo on brain waves, specifically alpha and beta [5]. Moreover, in their experiment done to study and compare the effect of classical and heavy metal music on the brain and cardiovascular system, Kalinowska et al. (2013) recorded EEG signals for 33 participants before, during, and after listening to Mozart's sonata K.448 (classical) and Iron Maiden (heavy metal) [6]. Yang et al. (2014) tried to prove Mozart effect scientifically by designing an experiment where the EEG is measured before, during, and after listening to Mozart's K.448 for 29 college students [7]. In another study, in 2012, Ahirwal and Londhe (2012) implemented a study to test the effect of visual attention on the brain's electrical activity through power spectrum analysis of EEG signals [8]. In a very different setup experiment, Lee et al. (2016) studied the EEG signals of subjects watching disgust-eliciting videos of disgusting creatures and body mutilation but with varying the auditory music. The videos were played two times; first with their original soundtrack, and then with relaxing music or exciting music and the original soundtrack muted [9].

Many types of stimulations have been used, including audible and visual ones. Music is a universal mode of auditory communication represented as sounds and vibrations. Music engages much of the brain processes; it evokes emotions whether positive or negative, connects to memory, and may trigger physical activities like dancing. Also, videos have been shown to trigger brain cells, affect brain focus and provoke brain activity changes.

In this article, we tend to examine the effect of music and video stimuli on the brain using the EEG. The main goal of this article is to detect any type of change in brain activity due to these stimulants. We propose a new approach in selecting the music and video stimuli in the fact that they are selected to be as much opposite as possible in order to be able to detect variety of changes within the brain.

2. Study Design

The methods we have adopted in this article for EEG signal treatment and time frequency analysis, are presented in this section.

2.1 EEG Recordings

In fact, there are several recording techniques used to detect functional and physiological changes within the brain including Magneto-encephalogram (MEG), Positron Emission Tomography (PET), and functional Magnetic Resonance Imaging (fMRI). However, EEG's main advantages over fMRI is its high temporal resolution. Like a high speed camera, EEG is capable of detecting the physiological changes that may occur within the brain in the orders of milliseconds. In addition, EEG is a completely passive recording technique, portable, light weight and relatively inexpensive [10]; all these make it the most accessible tool not only for medical diagnosis but also for neurobiological research.

Plenty of research studies have been conducted in order to understand different brain disorders by using EEG technology. Besides, several studies have been designed and implemented to test the effect of various external stimulations on the brain via EEG. These stimulations can be taken from our daily lives, and can be categorized depending on the goals of the study. Stimuli can be auditory like different types of music, binaural beats, and visual like flashlights, photos, videos, etc.

2.2 Placement of Electrodes

The electrodes are indispensable and irreplaceable part of an EEG machine. Various types of electrodes can be used to record EEG such as: headbands and electrode caps, disposable electrodes (gel-less, and pre-gelled types), reusable disc electrodes (gold, silver, stainless steel, or tin, saline-based electrodes, and needle electrodes. The number of electrodes is also variable from one system to another. It starts from eight, sixteen, and thirty-two, and it can reach over 200 electrodes.

Electrodes are positioned according to a standard methodology named "The International 10-20 System" that is recommended by the International Federation of Societies of Electroencephalography and Clinical Neurophysiology. By

using specific anatomical landmarks, the 10-20 system considers constant distances of 10% and 20% between electrodes. For this reason, each electrode is represented by a letter and a number. The letter denotes the cortical position the electrode must be attached to, such as: F for frontal, P for parietal, C for central, and O for occipital.

In our recordings, after ensuring the right positioning, 19 reusable cup gold-plated electrodes) are attached to the subject's scalp using a gel named "Ten20". According to the 10-20 International System, the electrodes cover all cortical lobes including Frontal (Fp1, F3, F7, Fp2, F4, F8), Temporal (T3, T5, T4, and T6), Parietal (P3 and P4), Central (C3 and C4), and Occipital (O1 and O2). Two electrodes are attached to left and right earlobes, named A1 and A2 respectively. An additional electrode is added on the forehead of the subject to filter the signal. After placing electrodes, the participant wears the earphones that are connected to a portable hp-PC where music and videos are played.

The referential/monopolar montage is used, in which the 16 channels represent potential difference between one active and one inactive reference electrode. The inactive electrodes are the one's attached to earlobes A1 and A2. The left hemisphere active electrodes are defined by their odd index (Fp1, F3, F7, T3, T5, O1, P3 and C3) and their reference electrode is A1. The right hemisphere active electrodes are defined by their even index (Fp2, F4, F4, T4, T6, O2, P4, and C4) and their reference electrode is A2.

2.3 Experiment Procedure

2.3.1 Experimental Environment

Subjects are asked to wash their hair the day before, and not to expose it to any kind of oils, gels, and chemical reagents. Subjects are forbidden to drink any source of caffeine (tea, or coffee) and alcohol 12 hours before the experiment. Subjects are also asked to get enough sleep on the day before

The experiment is done in a dark room. The participant is asked to sit down on an armchair and to extend his feet on a facing chair, so that he sits while his body is lying and relaxed. This helps us avoid any unnecessary movement.

Therefore, the number of artefacts in the acquired signal will be reduced. However, artefacts cannot be removed 100%. Therefore, to avoid its complications, we have used IC-Label. In this technique, objective statistical measures from ICs are computed and used therefore to decide automatically whether this component is artefactual or not [11]. 'IC Label' is a novel EEGlab-plugin which allows Automatic Artifact Rejection: It classifies ICs into brain and non-brain components determining specifically the contents of each component.

Using EEGLAB, independent component analysis (ICA) decomposition is applied to each EEG dataset, resulting in independent components of the same number of channels. The IC label is then applied to these datasets to detect which ICs are mainly composed of artifacts.

IC-Label classifies artifact components into 6 categories: eyes, muscles, heart, line noise, channel noise and more. And components containing neural information from the brain are called brain components. After the visual inspection of the classification given by IC-Label, the index of each artifact component is entered manually in order to be discarded, i.e. excluded from the dataset. The number of rejected components can vary from one dataset to another depending on the amount of artifacts present in each.

2.3.2 Experimental Signal Acquisition

For each subject, five separate EEG signals are recorded; each for 2 minutes. The total time is 10 minutes for each subject.

The 1st EEG recording is made while the subject closes their eyes and is not exposed to any auditory or visual stimulation. Subsequently, the stimulations are applied according to the following steps:

Video Part: The second and third EEG recordings are performed while the participant watches two consecutive 2-minute videos on the PC screen in front of him. The first video is of nature scenes accompanied by instrumental piano

music (Spring Flowers Inspiration, YouTube). The second video is of scenes of violence mainly killings and shootings (from the movie "Headshot", 2016). There was a thirty second pause between them.

Music Part: The 4th and 5th EEG signals are recorded simultaneously as the participant listens to two consecutive 2-minute music sections with a 30-second pause between them. First a section of Dubstep, Electronic Dance Music and then a section of classical music (Sonata Nb. 16 by Mozart). The participant is asked to close their eyes while listening to avoid blinking artifacts. Between the video and the musical part, a rest time is taken, two minutes, in which the participant can distract himself from any other activity.

2.4 Database

EEG signals are recorded for 56 healthy students using KT88 EEG Machine. The 21 males and 35 females' participants are aged between 18 years and 26 years (mean age 20.82 years). Subjects suffering from any neurological disorders or complications, or taking central nervous system depressants are excluded from undergoing the experiment. After obtaining the EEG recordings of all participants, 50 recordings among them are considered for further analysis. The recordings of 6 subjects (2 males and 4 females) are discarded due to errors and huge artifacts. The percentages of males and females remaining in the study, and whether they're right or left handed are given as follows; 38.0% males, 62.0% females, 86.0% right-handed, 14.0% left-handed.

Multiplying the number of subjects with the number of recorded signals for each subject, i.e. 50*5, gives us a total of 250 datasets. These EEG datasets are saved on the EEG software.

3. Signal Processing Phase

Since EEGLAB has more features than any other software, and it provides the user with a wide variety of signal processing choices [12], we have chosen EEGLAB to analyze and interpret the obtained EEG signals from the experiment.

3.1 Sampling

Converting the EEG signals to be in a digital form requires multichannel Analogue-to-Digital converters (ADCs). For this sake, the minimum sampling frequency allowed must be of twice the bandwidth of EEGs to satisfy the Nyquist Criterion ($Fs = 2*F$). Fortunately, the effective bandwidth for EEG signals is limited to approximately 100 Hz, and in many systems it may be considered to half this value. Accordingly, the minimum sampling frequency used is 100 samples/s. Other common sampling frequencies are 250, 500, 1000, and 2000 samples/s

3.2 Filtering

In order to get rid of the noise caused by several factors, high pass and low pass filters are both applied on EEG signals. The disturbing very low frequency noise created involuntarily, e.g. breathing, can be removed by applying high pass filters with a cut-off frequency of usually 0.5 Hz or even 1 Hz. Additionally, low pass filters with a cut-off frequency of approximately 50 up to 70 Hz are applied to remove high frequency noise. Notch filters with frequency of 50 Hz are also essential to reject the strong 50 Hz power supply

3.3 Pre-processing

Pre-processing of each signal was done before exporting them from the software. The signals are filtered with a band-pass filter, which is included within the software, of frequency range 1-40 Hz. This allows the exclusion of the noise of very low and very high frequencies. After filtering, the signals are exported in BDF format, and then introduced, one by one, into EEGLAB for the sake of analysis and interpretation.

3.4 Welch Method

For large datasets, the periodogram becomes statistically inconsistent method for estimating the power spectrum due to rapid variations with frequency, and leading to the presence of noise [13]. For the sake of reducing variance, Bartlett proposed dividing the signal into a number of non-overlapping segments, computing the periodogram for each segment, and then averaging periodogram [14]. Welch's method (1967) is an improvement of Bartlett's method. Welch has applied two basic modifications on Bartlett's method, first by allowing the overlap of segments, and second by windowing the segments before calculating periodogram [14]. Although Welch's method has the tradeoff of reducing spectral resolution, it is often desired to lessen the variance and make the power spectrum look smoother [13].

The data segments can be represented as:
$x_i(n)=x(n+iD)$ Where $n=0, 1…, M-1$; $i=0, 1…, L-1$; iD is the starting point of the ith sequence. L is the number of segments. If D=M the segments do not overlap. The modified periodogram becomes:

$$Px,(i)(f)= 1/M\ U\ |\Sigma x_i(n)w(n)e-2i\pi f n M-1 n=0|2$$

Where U is the normalization factor for the power in the window function:

$$U= 1M\Sigma w^2(n)M-1 n=0$$

Then, the Welch power spectrum estimate is the average of these modified periodogram which is shown as:
$$(f)= 1L\ \Sigma Pxx(i)(f)L-1 i=0$$

Since EEG is time varying, using the Welch method in estimating the power spectrum is more accurate than the classic estimation of periodogram (using Fourier Transform) [35].

3.5 PSD Calculation

After removing the components of non-neural origin, Fast Fourier transform is applied to the dataset. Then the power spectral density PSD of each waveform, delta, theta, alpha and 40 beta, is calculated for each component using Welch method. That is, for each component in a dataset four numbers, PSDs, are obtained.

In other words, the mean PSD of delta, theta, alpha and beta is calculated for each dataset, i.e. 4 PSD values are obtained for each dataset. Then, and as stated in [15], the relative power spectrum was computed. Then ANOVA test was applied to obtain if there a relationship between the stimuli and the brain rhythms. SPSS was used in order to perform the required ANOVA test.

4. Methodology

4.1 Flowchart and Neural Network Process

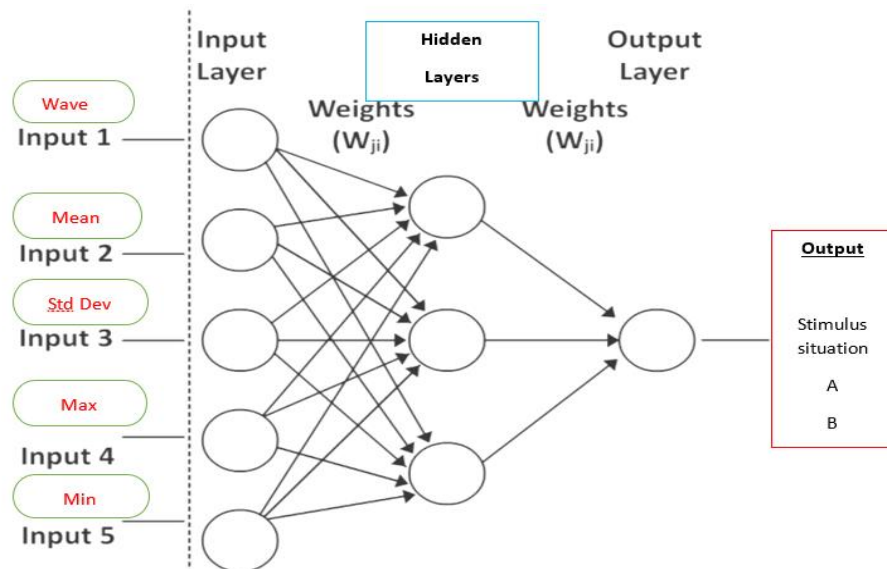The flowchart for the methodology is represented in Figure 1.

Figure 1: Flowchart of the Applied Method

4.1.1 Neural network model and layers

As can been seen in Figure 1, there are five input variables and one output variable (the last column). We will be learning a model to map rows of input variables (X) to an output variable (y), which is often summarized as y = f(X).

The input variables can be summarized using the following characteristics:

1. Wave: Five major brain waveforms, or brain rhythms, are distinguished by their frequency ranges: delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ).
2. Mean: the mean PSD of delta, theta, alpha, and beta is computed, i.e. 4 PSD values are obtained for each dataset
3. Std_dev; standard deviation of waves
4. Min: Minimum wave signal detection
5. Max: maximum wave signal detection

The output variable (y) can be described as follows:
Class variable for patient situation (stimulus): (A:0, B:1, C:2, D:3, E:4)

In Figure 2 we represent the usage and distribution of the input data. 70 % of the input data is used for the training phase, 20% for the testing phase and 10% for validation. For the training set, the output is obtained using a weighing coefficient and error is classified according to the 10% value. As for the testing input data, the outputs are obtained and the error is classified at the 2.5% value. On the validation data, errors are classified and prediction mode, discussed next, is exported.
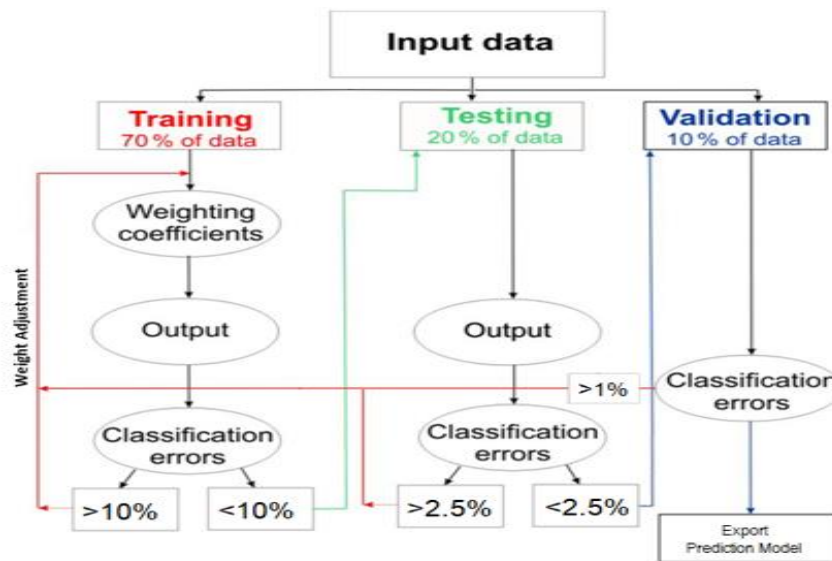
Figure 2: Input data distribution and output determination

4.2 Keras Model

Models in Keras are defined as a sequence of layers. We create a Sequential model and add layers one at a time until we got the best accuracy with our network architecture. The first thing to get right is to ensure the input layer has the right number of input features. This can be specified when creating the first layer with the input argument and setting it to 5 for the 5 input variables.

There are heuristics that we can use and often the best network structure is found through a process of trial and error experimentation we need a network large enough to capture the structure of the problem.

Fully connected layers are defined using the Dense class. We can specify the number of neurons or nodes in the layer as the first argument, and specify the activation function using the activation argument.

We will use the rectified linear unit activation function referred to as ReLU on the first two layers and the Sigmoid function in the output layer.

It used to be the case that Sigmoid and activation functions were preferred for all layers. The better performance is achieved using the ReLU activation function. We use a sigmoid on the output layer to ensure our network output is between 0 and 4 and easy to map to either a probability of class 1 or snap to a hard classification of either class with a threshold of 0.5. We can piece it by adding each layer:

- The model expects rows of input data layer with 5 variables (the input =5 argument)

- The first hidden layer has 50 nodes and uses the relu activation function.

- The second hidden layer has 25 nodes and uses the relu activation function.

- The third hidden layer has 10 nodes and uses the relu activation function.

- The output layer has one node and uses the Softmax activation function.

4.3 Compilation of Keras Model:

Compiling the model uses the efficient numerical libraries under the covers (the so-called backend) such as Theano or TensorFlow. The backend automatically chooses the best way to represent the network for training and making predictions to run on your hardware, such as CPU or GPU or even distributed.

When compiling, we must specify some additional properties required when training the network. Remember training a network means finding the best set of weights to map inputs to outputs in our dataset.

We must specify the loss function to use to evaluate a set of weights, the optimizer is used to search through different weights for the network and any optional metrics we would like to collect and report during training.

In this case, we will use cross entropy as the loss argument. This loss is for a binary classification problems and is defined in Keras as "binary_crossentropy ".

We will define the optimizer as the efficient stochastic gradient descent algorithm "adam ". This is a popular version of gradient descent because it automatically tunes itself and gives good results in a wide range of problems. To learn more about the Adam version of stochastic gradient descent see the post.

Finally, because it is a classification problem, we will collect and report the classification accuracy, defined via the metrics argument.

The training process will run for a fixed number of iterations through the dataset called epochs, that we must specify using the epochs argument. We must also set the number of dataset rows that are considered before the model weights are updated within each epoch, called the batch size and set using the batch size argument.

For this problem, we will run for a small number of epochs (1000) and use a relatively small batch size of 10.

These configurations can be chosen experimentally by trial and error. We want to train the model enough so that it learns a good (or good enough) mapping of rows of input data to the output classification. The model will always have some error, but the amount of error will level out after some point for a given model configuration

We have trained our neural network on the entire dataset and we can evaluate the performance of the network on the same dataset.

This will only give us an idea of how well we have modeled the dataset (e.g. train accuracy), but no idea of how well the algorithm might perform on new data. We have done this for simplicity, but ideally, you could separate your data into train and test datasets for training and evaluation of your model.

You can evaluate your model on your training dataset using the evaluate() function on your model and pass it the same input and output used to train the model.

This will generate a prediction for each input and output pair and collect scores, including the average loss and any metrics you have configured, such as accuracy.

The evaluate() function will return a list with two values. The first will be the loss of the

model on the dataset and the second will be the accuracy of the model on the dataset. We are only interested in reporting the accuracy, so we will ignore the loss value.

5. Results

In this section the results of our experiment will be presented and discussed.

5.1 Prediction Making

We start this section by presenting the results of the prediction model.

Making predictions is as easy as calling the predict() function on the model. We will import the generated module (Multi.h5) from the loaded class MultiClass.py and using a different value of the below arguments in this model such as:

Model (A):

- Module Activation: sigmoid activation function on the output layer

- Hidden Layers: 3 hidden layers with relu activation function

- Kernel_initializer: 'random normal' is a function to use for initializing the weights.

- Optimizer= tensorflow.keras.optimizers.Adam(learning_rate=0.01)   is an extended class, which include added information to train a specific model and used for improving speed and performance for training model.

- epochs=1000 and batch_size=50

The accuracy ration in this module is as below: 0.688 %

Model (B) with ADAM optimizer:

- Activation: sigmoid activation function on the output layer

- Hidden Layers: 2 hidden layers with relu activation function

- Kernel_initializer: 'random_normal'

- Optimizer= tensorflow.keras.optimizers.Adam(learning rate=0.01)

- epochs=1000 and batch size=50

The accuracy ration in this module is as below: 0.695 %

Model (C) with SGD optimizer:

- Activation: sigmoid activation function on the output layer

- Hidden Layers: 2 hidden layers with relu activation function

- Kernel_initializer: 'random_normal'

  - Optimizer= tensorflow.keras.optimizers.SGD(learning_rate=0.01)

  - epochs=1000 and batch_size=50

The accuracy ration in this module is as below: 0.172%

5.2 Data Source from ANOVA Result:

Table 1: ANOVA Results

Wave	Stimulus	Mean	Std. deviation	Minimum	Maximum
1	A	1.6641	0.2453	0.4265	0.0213
	B	0.5662	0.0696	0.072	0.0193
	C	1.6865	0.124	0.0973	0.0357
	D	0.7841	0.9368	1.2013	0.0679
	E	1.1732	0.5273	0.4096	0.0266

2	A	3.1273	0.4284	0.434	0.0861
	B	2.6902	0.2429	0.2765	0.0986
	C	0.8126	0.1527	0.1988	0.0713
	D	1.1932	0.5473	0.5096	0.0766
	E	1.1032	0.6251	0.6019	0.0728
3	A	0.4982	0.2178	0.7885	0.0457
	B	0.2394	0.1038	0.1195	0.0279
	C	0.2168	0.0971	0.1154	0.031
	D	0.4841	0.2368	1.0013	0.0579
	E	0.4386	0.2134	0.7645	0.0471

6. CONCLUSION and FUTURE WORK

In this paper, we study the effect of different stimulus on the brain activity in an attempt to discover the reactions of the brain. This work investigated the impact of listening to heavy and classical music on brain activity using EEG recordings. A control experiment was performed by recording EEG without stimuli. The four brain waves were studied.

Neural network process has been proposed to obtain outputs of the stimulus. The input variables are the five major brain waveforms, the mean PSD of delta, theta, alpha, and beta waves, the standard deviation of waves, the minimum wave signal detection and the maximum wave signal detection.

A prediction model was developed based on Keras model. The accuracies were computed for three m models proposed; Model A, Model B with ADAM optimizer and Model C with SGD optimizer.

ANOVA test was done to determine the relationship between the waves applied and the various stimuli (A, B, C, D, E). The mean, standard deviation, minimum and maximum were calculated for each wave-stimulus pair.

The aim of the study is to collect different values of ANOVA signals after various stimuli, so that the patient's condition in general can be estimated, which will help medical teams to receive direct notification of contemporary diagnoses or unexpected measures.

Several limitations have been detected in our study and may have affected our results, including the short time of applying the stimulations, the large number of artifacts in the EEG signals

Further work can be done using EEG recordings to study other features and characteristics of the effect of stimulations on brain activity. There may be more specific design for use in future work such as considering other music stimuli by combining only two genres. Moreover, the effect of music on healthy and unhealthy subjects can be compared. The study thus will include healthy subjects and subjects with certain brain disorders. Furthermore, due to their high accuracy in the analysis of time-varying signals, additional research on EEG requires the use of feature extraction tools such as wavelet transform and approximate entropy.

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