Available online at sjuoz.uoz.edu.krd

journals.uoz.edu.krd

Science Journal of University of Zakho

Vol. 10, No. 1, pp. 16– 23, January – March, 2022

p-ISSN: 2410-7549
e-ISSN: 2414-6943

BRAIN WAVES SIGNAL MODELING FOR OBJECT CLASSIFICATION USING RANDOM FOREST METHOD

Younus H. Mala [a,*], Mahmud A. Mohammad [b]

[a] Faculty of Science, University of Soran, Soran, Kurdistan Region, Iraq (yunis.mala@soran.edu.iq)
[b] Faculty of Science and Technology, University of Human development, Sulaymaniyah, Kurdistan Region, Iraq – (mohammad.mahmud@uhd.edu.iq)

Received: *05 Jan., 2022 /* ***Accepted:*** *01 Mar., 2022 /* ***Published:*** *08 Mar., 2022* ***https://doi.org/10.25271/sjuoz.2022.10.1.876***

ABSTRACT:

In this research, the connection between human vision information and simultaneous brain signal is studied; to this end, an experiment has been made. Clearly, brain wave signals are captured in the situation that the participants are looking at the specific object. More precisely, the brain signals of 9 shapes are recorded for each participant. Also, 9 participants voluntarily have been involved in the experiment. Then, the collected signals are organised into training and testing groups. After that Random Forest classifier is used to classify the signals.

The accuracy results demonstrate a connection between human vision information and simultaneous brain signal. Overall accuracy for all shapes as separated as per cases is 20.48%, and for shapes, numbers 6 and 8 are 55.34% 36.57%, respectively. It can be concluded that human brain signals can be categorised based on human vision inputs.

KEYWORDS: Brain Signal, Signal Processing, Machine Learning, Human Vision.

1. INTRODUCTION

The brain is one of the main and most complicated organs in the human body. It contains three main parts: cerebrum, cerebellum, and brainstem. The main part of the human brain is the cerebrum, according to 85% of the organ's weight, and it is made of four lobes: frontal, parietal, temporal, and occipital. The frontal lobes are responsible for solving problems, decision-making, and motor function: the parietal lobes direct body location, handwriting, and feeling. The chronological lobes are elaborated with memory and hearing. The occipital lobes handle visual processing and object recognition (Barroso, 2014) (Tonya, 2018).

The human brain constantly produces large electrical actions, these signals are non-stationary, and they can be estimated by various tools, including functional magnetic resonance imaging (FMRI), electroencephalogram (EEG), and magnetoencephalography (MEG). These tools directly extract some brain signal features form into a number of different bands; alpha, beta, delta, gamma, and theta are the five bands of brain signals. Furthermore, among the aforementioned tools, EEG is a cheap and straightforward way to record brainwave signals compared.

In addition, the EEG signals have been used for analysing several vision-based works; these works are based on the visual content of the scene, such as visual memorability, known and unknown faces classification, scene classification, a visible object to control the movement of a wheelchair. Furthermore, using EEG signals to understand the scene at the object level is vital; this led to better monitoring and controlling the elderly centres than CCTV. Although applying computer vision methods on CCTV footage is considered a noticeable monitoring improvement, it is difficult to cover all points in the room when someone moves around in different directions. Thus, as the first step toward scene understanding, object classification is investigated in this research.

Along with, due to the difficulties of obtaining a proper device, the single-channel MindWave mobile2 has been used, manufactured by Neurosky Inc.. The device is made up of two sensors that detect and filter EEG signals. Electrical impulses are detected by one sensor put on the forehead; it is utilized to recognize the EEG signals. This sensor collects noise from the surrounding environment, produced by the muscles of humans, lights bulbs, compute, etc. Also, it has a clipped ear that can be placed in the ear and is utilized as a reference for the electrical noise to be filtered out.

Moreover, the device gathers raw EEG signals, with the range of 512 Hz in the power spectrum (alpha, beta, delta, gamma, and theta). Importantly, the Mindwave sensor is positioned in the left side of the forehead, the position of Fp1 (Dzaferovic E. et al., 2017). The frontal lobe is a part that has FP1 to be obtained from by a sensor that the signals are obtained, and it is responsible for personality, behavior, emotions, judgment, planning, problem-solving, speaking and writing, body movement, intelligence, concentration, and self-awareness (Tonya, 2018).

The remainder of the paper is structured as follows: Section 2 provides the related works. Research methodology is presented in Section 3. Data recording software is described in Section 4. Section 5 explains scenario setup and data collection. Experiments and results are presented in Section 6, and the research is concluded in Section 7.

2. RELATED WORKS

Today, EEG is utilized in many technical areas such as health, computer games, natural language processing, and education (Tajdini et al., 2020). Thus, several recent works in this area are explained in detail.

A study has been conducted by (Zhou et al., 2020). for sleep stage classification, and they divided the sleep stages into six different stages: wakefulness (W), Non-rapid eye movement (NREM), N1, N2, N3, N4, Rapid eye movement (REM). Visual inspection Polysomnography (PSG) is used by experts for recording. An

* Corresponding author

automatic sleeping stage system is developed, which is a single-channel electroencephalogram (EEG) signal. This study recommends a two-layer stacked ensemble model that connects the advantages of random forest (RF) and LightGBM (LGB). Random forest reduces the variance, and Light-GBM reduces the bias of the proposed model. The study model worked on two datasets, including the Sleep-EDF database, whole night sleep (SEDFDB), for the participants aged from 21 to 35. The total number was 8 (4 male and four females, divided into two groups) who were fully in sleep; for both of the subsets, there was data of 2 EEG channels (EEG Pz-Oz, EEG Fpz-Cz) one horizontal EOG signal have been gathered. The data gained from a rating sample of 100 HZ manually were divided into six groups. Sleep-EDF Expanded database, which is day-night sleep, 197 recordings have been done on 78 participants (34 males and 44 females, divided into two different groups) aged from 25-101. whole-night sleep PSG recordings consisted of EEG (from Pz-Oz and Fpz-Cz electrode locations), EOG (horizontal), submental chin EMG, and an event marker; the PSGs recorded in the hospital for two nights in 9 hours, data were gained by 100 HZ rating sample and manually divided into the six groups. Sleep awake disorder (SEDFEDB). In the SEDFDB, the overall accuracy (ACC) is 91.2%, weight F1-score (WF1) is 0.916, Cohen's Kappa coefficient (Kappa) is 0.864, the sensitivity of N1 (SEN-N1) is 72.52% obtained by the proposed model conducting the subject-non-independent test (SNT). Similarly, by the study model, the ACC is 82.4%, WF1 is 0.751, Kappa is 0.719, SEN-N1 is 27.15% are obtained by using a subject-independent test (SIT). This study has used N-Point Fast Fourier Transformation (FFT) to estimate the frequency of every frame with state-of-the-art methods; experimental findings demonstrate that the performance of the suggested model is competitive, and the identification rate of N1 stage is expressively improved. Furthermore, in the SEDFEDB, the finding of the experiment shows the strength and generality of the suggested model. This study offered a wearable system of home sleep monitoring.

Likewise, (Chen et al., 2019) have conducted a study on the relation between attention and emotion signals; previous studies have shown that there wasn't any difference between emotion and attention. This study developed a new system named Deep Focus. The evaluation method of this study is based on two multi-modal data, which contains an eyes tracker for eye movement, brain wearable signals for reading EEG signals, and a video camera used to capture the users' facial expressions. The second method is Multi-scenario behavior analysis; it is based on four scenarios: working its accuracy recognition is 0.981, studying its accuracy recognition is 0.413, relaxing which its accuracy recognition is 0.878, and amusement scenario recognition accuracy is 0.984. This method is used to measure real-world activities. The equipment is used for this study are a computer, video camera, headband and the brain loop NeuroSky for analyzing the scenarios. A traditional feature extraction which is Short-time Fourier transform (STFT), is used to transfer the EEG from time sphere to frequency sphere; rhythm waves (α, β, δ, γ, θ) are taken out. A brain wearable device that is a one-route EEG gatherer is conducted to gather the data from the four scenarios. A band-pass filter is used to filter the low-frequency and high-frequency components, and for eliminating the noise, independent computer analysis (ICA) is used. Support vector machine (SVM) is used to classify the level of attention of the recorded videos on the four scenarios. This study demonstrated that there is a strong relation between emotions and attention based on classifications of EEG signals.

Also, based on human vision, (Jo et al., 2020) have been made an experimental paradigm on the study of visual memorability to investigate how to estimate the way media subjects and images can be memorized. This study has conducted based on the human biological assessment (EEG). The study has passed under two sessions learning sessions and testing sessions on 21 participants (14 males and seven females) aged between 20 and 26. In the learning session, the participants are asked to look at the image for one second; in this session, 160 images were shown to them. A visual memory task is designed, and after 30 minutes of glancing at images then, each participant is asked whether they remember a special image or not by showing them 160 images in the learning stage and 160 new images that they have not seen; the participants are asked to mark "O" if they thought they have seen the images and mark "X" if they did not have seen the images in the learning session. In the pre-processing stage (SNR), a signal of decreasing noise ratio is conducted to lower the noise. For gathering Raw EEG signals, Bandpass filtering and re-referencing strategies were adapted. During the task, the EEG signals, which are human biological feedback of each participant, are recorded. The images obtained from the two sessions (learning and testing) are from a dataset of large-scale image memorability LAMEM; this dataset contained 60,000 different images. For expecting image memorability, the gathered EEG signals are utilized for training different models of classification. For recording EEG signals, a 32 channel Emotiv Flex tool, an EEG recording equipment produced by a company of EMOTIV placed in San Francisco, USA, with a sampling of 128 Hz frequency and Emotiv Pro software, were utilized. The positions of the electrodes utilized in this research were modified as F1,2,5,6,9,10,z, FC1,2,5,6, FT7,8, C5,6,z, CP1,2,3,4, TP7,8, P1,2,3,4,z, PO7,8, and O1,2,z under the system of 10–10.

Also, in their study, two models were used for the model of classification: traditional machine learning algorithms and advanced deep learning networks. Traditional machine learning like support vector machine, logistic regression with stochastic gradient descent training (SLR), decision tree, and k-nearest neighbor are utilized. For the deep learning model, shallow and Deep ConvNets are used. Before the final classification layer, Deep Convent is used to determine the signals of EEG classification into two states: "remembered" and "forgotten". Based on the 10-folds cross-validation of an experiment and based on the two models of deep learning and traditional machine learning based on their classifiers, the results were equivalent, which are 68% from Shallow ConvNet and 69% from the classifier of random forest. The study showed that EEG signals were still challenging because the memorability prediction is not stable from the same person on the same day. Brainwaves are also not reliable because of the mental health of the participants.

Furthermore, (Azar et al., 2014) worked on the Brain-computer interface (BCI), which is a support system to control the movement of a wheelchair for those patients who are neurologically disabled by using their (EEG). A total 90 trials were conducted during the whole study for each participant. By imagining the participants to move his/her hand imaginary by EEG signals of the oscillations by the classification of BCI. BCI will translate the patient's thoughts into two commands, "GO" and "STOP", the EEG signals are recorded by using 59 electrodes of scalp, according to the system of channel locations which is 10/20. The signals were tested in 100HZ. Two activities were conducted, imagined right-hand and imagined left-hand movements. The achieved signals remove the artifacts: eye movement, eye blink and heartbeat, and other muscles' activities by using the Blind source system (BSS) by independent component analysis (ICA). For feature extraction, the discrete wavelet transformation (DWT) is used because it can keep the information for a longer time and localize the newly existing signals easily compared to Fourier transform that much information can be lost there. After that, the new EEG signals and artifacts were obtained. Digital signal processing (DSP) can be used to find out the features of EEG signals of each patient. For the classification, the nonlinear neural network is implemented.

Three unseen neurons implemented the network in the unseen layer, and in the output layer, a single neuron is implemented that 0-1 was an expected result that came from it. "Leave-K-Out" was used for the method of cross-validation. The principal component analysis (PCA) is used to reduce dimensionality after the features are extracted. The neural network classifiers are used to feed the extracted features its classification that resulted in 95% of its accuracy. The findings showed that this system could be useful in the field of medical decisions because the data can be obtained in a shorter time and in a detailed way.

In addition, (Nair et al., 2018) have proposed a known and unknown faces classification model based on EEG signals. The study has proposed a deep learning-based classification of EEG signals. The total participants were ten aged between 22-25 years. Without having any neurological or health problems, their vision was quite normal. The participants have shown the known and unknown faces in the experiment. The participants have shown a familiar image, then after 5 minutes, the unfamiliar image or face was shown. This act was repeated two times in each session,2 seconds were given for each image, and each subject had 20 seconds for each task. Total familiar images were nine images of the famous personalities they know well and nine images of some people whom participants did not know. The participants were sat in a chair in front of the monitor, and the distance between them was 65cm. An EEG Headset with eight electrodes system was used for the data achievement aim. The positions of the electrode were Fp1, Fp2, C3, C4, P7, P8, O1, and O2. According to the International 10-20 electrode system, the sampling frequency recording was 256HZ. Then Independent component analysis (ICA) is used after processing which is also used as feature extraction. The study is divided into three stages: data collection, signal processing, and classification. For classification, by autoencoder, the signal has fed. After the model had been worked on properly, the total mean was 82.21%, which was much better than the models using conventional machine learning methods.

What is more, (Ullah et al., 2019) conducted a study to determine internal human emotions by using EEG signals and Kernel-based representations, a type of support vector machine (SVM) for training recordings of EEG. The signals of EEG were taken from 32 participants; they watched 40 examples of music videos in a one-minute duration. Under the 10-20 international standards, the electrodes were placed on the scalp of the participants. Also, another eight channels are used to record other peripheral psychological signals like respiration rate, skin temperature, galvanic skin response, electromyogram, electrooculogram (horizontal and vertical), and blood volume pressure. The objective function of Linear discriminant utilizing kernel representations is used for ensemble learning. Spare non-negative Principal Component Analysis (PCA) is used for solving objective functions proficiently, and by using the sparse projection coefficients, the final classifier is obtained. Ensemble learning algorithm is beneficial in decreasing the quantity of data while at the same time developing computational effectiveness and accuracy classification. The feature extraction has passed under three stages, short-time Fourier Transform (STFT), The Discrete Cosine Transform (DCT), and Spectrogram-based features. downsampling, bandpass filtering, and EOG removal are utilized in the pre-processing stage. The experiment results showed that the dataset of EEG illustrated the highest power by the proposed algorithm, which is ensemble learning compared to the other methods. The findings demonstrated that the proposed method, which is SDEL has better performed with comparison to the other simple classifier methods because of its discriminative choice of channel; the emotions were classified and measured by two classifications which are Arousal and Valence. The results for each individual channel were like that: K-NN (sum score fusion) was 60.4% and 55.4%, SVM (majority voting) was 63.1% and 59.1%, SVM (channel fusion) was 62.3% and 56.2%, K-SVM (average kernel) was 66.7% and 64.7%, and the highest rate was recorded by the proposed model which is SDEL that its Arousal and Valence were 70.1% and 77.4%.

A study conducted by (Khade et al., 2017) used brain waves signals for scene classification; the dataset is captured by the EGG tool by putting electrodes on the scalp to quantity the brain signals used. By having each scene and object, the changed EEG signals are decoded. For analyzing the signal, the study used independent component analysis, event-related potentials, and the grand mean. The study used machine learning algorithms like support vector, decision tree, and random forest to categorize the data. Linear finite impulse and ICA are used to react filtering for eliminating noisy data which is unwanted. Fourier transform is used for feature extraction for transforming data signals, wavelet transform (WT) is used to apply time-frequency domain which is known as an infinite range of wavelets. The original signals are known as safe and straightforward blocks that are recognized as wavelets. As part of the derivative function is when a big or mother wavelet spreads growth to these wavelets through conversion and dilation, Shifting firmness, and extending operations on the axis of the period. The study results are useful for forensic and artificial intelligence for growing future technology.

Classification of a number of patient types is studied by (Fiscon et al., 2018), based on a procedure that adapts feature extraction and classification techniques to signals of EEG; the aim of the study is to recognize the patient influenced by Alzheimer disease (AD) from those that influenced by Mild Cognitive Impairment (MCI) and samples of Healthy control (HC). Particularly, time-frequency analysis is performed using Fourier and Wavelet transform on 109 participants who belonged to AD, MCI, and HC classes. The study adopted a decision-based tree for classification. The classification process is designed into some steps like (i) pre-processing of EEG signals, (ii) feature extraction by Discrete Fourier and Wavelet Transforms means, and (iii) classification with tree-based supervised methods. The study results showed the ability to recognize patients with the class that they belong to, importantly, in an automatic way. Especially, by manipulating a Wavelet feature Extraction, the study results attain an accuracy of 83% for HC vs. AD, 92% for HC vs. MCI, and 79% for MCI vs. AD when dealing with classification issues. The study conclusions displayed that the wavelet analysis outdoes Fourier. Thus, based on the EEG signals, the study suggests the connection with the supervised methods for automatic classification of patients for supporting the medical analysis of dementia.

As a connection between thinking about and seeing a shape, (K. Rostam et al., 2019) conducted a model on convolutional neutral network (CNN) to categorize a brainwave signal. The aim was to assess the activity of the suggested model. A dataset was presented by taping brainwave signals into two types: Visible and invisible. In the visible mode, the human participants were concentrated on the shape and colors displayed. On the other hand, in the mode of invisible, with closed eyes, the participants think about the particular color and shapes. Coming to the contrasting, a method of comparing the architecture of an original (CNN) and suggested (CNN) on a similar dataset has been given. The study has conducted ALPS and GA to identify the population sample for the study; the ALPS-EA has worked by the algorithm first to recognize the age layer to construct and assess the initial random population after that, the ALPS-EA goes to its major loop that contains cycling over layers finally affiliating the EA in that layer for one generation. The convolutional neural network is used between the input data and Filter (Kernel). An activation method is practiced on either convolved volume normally rectified Linear Unit (RECLU), the pooling layer performs as an extractor applied on the results.

Their study selected the newest version of the NeuroSky mind wave mind wave mobile two. The participants were six with a normal color sigh and normal brain health that each aged between 30 +/- 5. They sit on a comfortable chair in a dark room with a screen of 43 inches. The distance from the screen was 125 centimetres. The screen was normal in its features. The main classification of the dataset was color and shape with two subcategories (visible and invisible). The time duration for each session was 25 seconds with having five-session recordings for subcategories as a result; the dataset consists of 6000 seconds of brainwave signals, each sub-session containing 750 seconds. For each mode, there are two either colors or shapes available; the entire duration for each mode colors or shape is 1500 seconds separately. Hence, the total duration is 3000 seconds. The data is stored by Comma-Separated Value (CSV) for each individual within each sub-session. Discrete wavelet transform (DWT) coiflet is used for transforming the feature extraction signals in this proposed model. The findings demonstrated that the suggested CNN obtains higher categorization accuracy while contrasted to the original one. Importantly, the best rate of accuracy is achieved while the suggested CNN is practiced on the mode of visible color, which is 92%. The study gives expectations for the future that the developments of the suggested CNN will be capable of categorizing raw EEG signals in an effective way.

Again, different machine learning methods are used by (Zheng et al., 2014) to display a dependable model for classifying two emotional classes (positive and negative) constructed on progressive deep learning method. A data set was created from recording brainwave signals from 6 participants, two trials for each participant at an interval of one week or longer. To test the algorithm and predict the emotional state, sixty-two (62) EEG channels were utilized while the individual watched movie clips emotionally. A deep belief network (DBN) was adopted during the training, from multichannel EEG features were extracted. For classification appropriately, a hidden Markov model (HMM) was combined with DBN to capture switching the stages of emotion. The researchers of the study offered a comparison of performance between deep models of K-NN, SVM, and Graph Regulated Extreme Learning Machine (GLEM). accuracies were attained of K-NN was 69.66%. , DBN–HMM was 87.62%, DBN was 86.91%, SVM was 84.08%, and GLEM was 85.67%, and outcomes demonstrated that when the dataset was tested with DBN– HMM model then, the major accuracy was attained.

Lastly, (Siradjuddin et al., 2017) have proposed a model built on a Genetic Algorithm (GA) for recognizing alcoholics utilizing signals of EEG. UCI (University of California Irvine) machine learning repository has been used as a dataset. As long as the dataset was recorded from 64 electrodes with a sample rate of 256 per second, there are 64 channels in the dataset. The dataset contains EEG data for ten alcoholics and ten normal individuals. The research passed by four steps. First, Independent Component Analysis (ICA) was used for separating signals and noise removal. Second, the Discrete Wavelet Transform (DWT) was utilized for a feature extraction that classifies signals into low frequency (approximation) and high frequency (detail). Third, the extracted features from DWT were fed to the GA; as a feature selector GA was implemented, this stage increased the accuracy of recognition by selecting the best grouping of features for the alcoholic detection. Finally, the designated features were fed to the backpropagation neural network. 79.38% was the total accuracy of alcoholic detection that was attained.

To sum up, as listed in the table (1), the above research works can be classified into two groups. First, non-vision-based works consist of these research works that have no connection with the visual content of the scene, for instance: sleep stage classification, the relation between attention and emotion signals, determining the internal human emotions, recognizing alcoholic and non-alcoholic people. Second, vision-based works consist of the research works that are based on the visual content of the scene, such as visual memorability, known and unknown faces classification, scene classification, a visible object to control the movement of a wheelchair.

Table (1): represents a summary of the related works

Author (s)	Application	Vision-based
Zhou et al. 2020	Sleep Stage Classification	No
Chen et al. 2019	Relation Between (Attention And Emotion) Signals	No
Jo and Jeong,2020	Memorized	Yes
Azar et al. 2014	Control The Movement	No
Nair et al. 2018	Known and Unknown Face Classification	Yes
Ullah et al. 2019	Emotion	No
Khade and Ilakiyaselvan 2017	Scene Classification	Yes
Fiscon et al. 2018	Alzheimer Disease	No
K. Rostam and Mahmood 2019	Classified Signals. Controlling An Electronic Device	Yes
Zheng et al. 2014	Positive And Negative Emotional	No
Sirajaddin et al. 2017	Detect Alcoholic	No

Focusing on the second group, a visible object to control the movement of a wheelchair is specified for the patients that are neurologically disabled, which means the study is specified for non-healthy people. Also, known and unknown faces classification is a specific aspect of visual memorability, the visual memorability means memory retrieval for a specific object. Obviously, a normal scene consists of many objects, thus it is crucial to classify and recognize these objects. However, scene classification is an important start toward understanding the scene; it is a high level of information compared to the object level.

Thus, on the basis of the previous studies, it has been noticed that there is no research focusing on the object classification of the scene; this is to prove the strong connection between the visual content of an image and brain signal produced by healthy people. Thus, this study proposes a problem to find a connection between human vision when looking at the object in the scene and the produced signal of the brain. To this end, an experiment has been made which is focused on object classification on the basis of brain signals.

3. CLASSIFICATION METHODS

For brain signal classification many algorithms were used by other researchers such as Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbor (K-NN), Genetic Algorithm (GA), Convolutional Neural Network (CNN), Deep Convolutional and Shallow, Light GBM (LGB), Simple Linear Regression (SLR), Non-linear Neural Network, Autoencoder, and Hidden Markov Model in combination with Deep Belief Network (DBM-HMM).

In this work, a random forest classifier (Breiman et al., 2001) has been selected to perform the classification that includes multiple decision trees (Kim. H et al., 1995); using bagging classification, the method produces overall classification for unseen sample.

According to the random forest theory, each decision tree from the bagging pool is built based on features of the available training samples, and then the trees are constructed in a top-down form. More interestingly, there is no pruning of the decision trees, which led to exemplary learning from the training samples.

More precisely, a random forest classifier is a supervised machine learning algorithm built based on the algorithm of decision tree. So, this algorithm is utilized in different industries like banking and e-commerce to expect behavior and its consequences. As a machine learning technique, a random forest is utilized to cure regression and the problems of classification. It adopts ensemble learning, a method that links a lot of classifiers to offer solutions to complicated problems. A random forest algorithm contains a lot of decision trees. Hence, the "forest" produced by the random forest algorithm is accomplished over bagging or bootstrap accumulation. So, bagging is an ensemble meta-algorithm that develops the truthfulness of machine learning algorithms.
Therefore, based on the expectations of the decision tree, the random forest algorithm recognizes the consequences. Hence, taking the average or mean of the different trees' results gives its predictions. Moreover, the accuracy of the results is increased by increasing the number of trees.
On the other hand, the shortcomings of a decision tree algorithm are eradicated by the random forest. It also decreases the over fitting of data sets and raises the trustfulness without needing a lot of recognition from the packages. (Onesmus Mbaabu, 2020).

4. DATA RECORDING SOFTWARE

To improve the research validity, a program is needed to connect EEG devices to the computer, receive brain signals, and record them. The software was successfully developed that meets all of the needs of the current study and requirements. The study implemented and employed a data collecting GUI tool. The tool is implemented with Microsoft C#, having WPF as its user interface. The tool will be called "Brain Reader (BR)", and the final version of it is referred to BR4.0. The tool has an external connective tool that enables the mind wave reader (Mind Wave Mobile2) to be connected with pc via an in-built Bluetooth. The main parts of the software interface are listed as below:

a) Condition Class: it creates signal filters for readings from the device.
b) Connection Class: It connects the wave reader device to the computer with the support of the Native Think Gear channel.
c) Scenario Class: creates new scenarios that hold conditions and sequences.
d) Sequence Class: stores a sequence of readings from the connected device.
e) Serializer Class: it is an object read and write to the standard input/output system.
f) Signal Class: create an instance for readings that are valid.
g) Vision Class: to monitor the results with charts and figures.

All the brain activities were shown through the software screen. The raw EEGs, signal qualities, attention, meditation, and bands (alpha, beta, delta, gamma, and theta) were shown separately and plotted on the software screen.
As shown in figure 1, each scenario can be saved or imported to or from a file with the help of serializer objects. A scenario consists of filtering conditions, several sequences, a connector, and visualization objects. Each sequence has read signals from the device that later are compiled for observation and movement detections. Figure 2 shows the connection between classes and their mechanism.

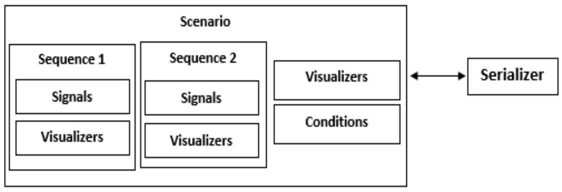

Figure 1. Class Diagram of Brain Reader Version 4.0

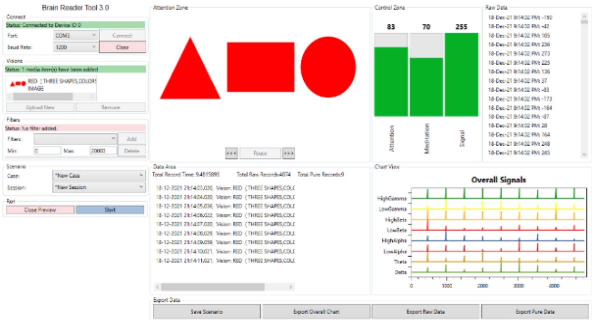

Figure 2. BR4.0 main window

Furthermore, there are various features provided by the brain reader device that make the data collection mechanisms more convenient for this work. For instance, the user can set a period of time to register the data read from the device. Additionally, the software provides a feature in which users can ignore all readings that do not have efficient signal accuracy. Moreover, the users are able to select the recording timeframes and when to start and end readings. The usage of this tool remains straightforward, and all the steps are shown to the end-user in clear texts. First, the user imports videos or image files that have been selected for brain signal comparisons. Later, they might select a few features to be filtered and selected for the next readings. Afterward, the connection to the device is checked, and readings start. The software provides a double screen for both the researchers and the candidates. Anytime the readings are strong enough to be counted as significant readings, the user can start recording and creating new sequences. The BR4.0 is explicitly and specifically designed for this study, and it is not shared publicly.
All the data have been obtained in a second in raw EEG data with the rate of 512 Hz (Sałabun, 2014).
After obtaining the signals, the software converts the CSV files to the bands of alpha, beta, delta, gamma, and theta and the raw data file.

5. SCENARIO SETUP AND DATA COLLECTION

In this study, the latest version of Neurosky mind wave is implemented for the mind wave mobile2 to transfer the EEG signals as the main source of data received at 512 HZ. (Pal et al., 2020). Figure 3 demonstrates the device.
This study receives data from 9 participants aged 27 to 45 years to construct a data set. All the participants were in normal vision condition, and they were in a normal state of mind. The process of receiving signals from one of the participants is presented in figure 4. Also, a record of the Gamma EEG band for a participant is shown in Figure 5. Gamma wave has a range of 30HZ and above. It has a high cognitive activity, known as motor function. The Gamma pace has received great attention. It is known as a moderated sensory input and a process that is internal, like attention and working memory (Hima C. S. et al., 2015).

Figure 3. Mind wave mobile2

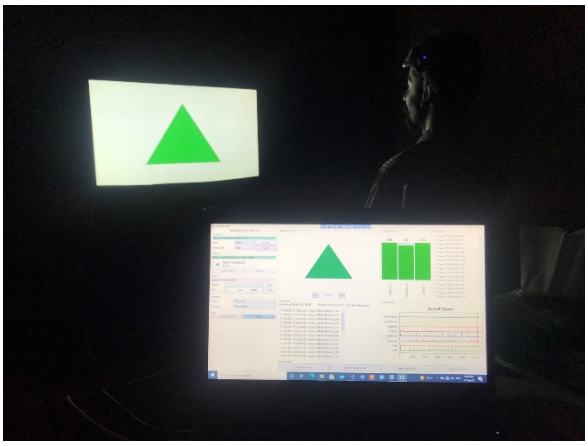

Figure 4. process of receiving signals form one of the participants precented

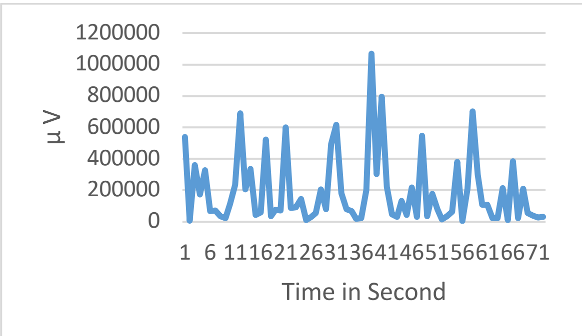

Figure 5. illustrates 72 records of Gamma EEG band, for all participants, and all shapes in different colors.

Before starting the process of receiving signals from the participants, they were given an instruction slip on how to do the process successfully; the instructions included whether the participants were in stable sleep the previous night, and focusing their attention on the objects, ensuring that they do not have any health problems or body pain while obtaining the samples from them, keeping avoidance of blinking and body movement, and not to bring any electronic devices with them into the room of the experiment. Also, some extra information was gathered from the participants like age, gender, problem-solving capability, sicknesses such as head diseases, anesthesia, and coronavirus infection. The device was placed on the participants' heads, and a scenario was shown to the participants in a comfortable area from a distance of 1.5 meters from the 42-inch TV screen; the screen was set to a normal mode of brightness, color, and contrast.
Each participant was shown eight objects that consisted of different shapes with different colors (green circle, blue circle, red circle, green rectangle, blue rectangle, red rectangle, green triangle, and red triangle rectangle circle). Also, each participant had given five sessions recording for each shape and color, and each session was recorded for 25 seconds. For each participant, 125 seconds were given for recording each shape. Also, for the eight objects, 1000 seconds were given, and the total for the 9 participants was 9000 seconds, which is 150 minutes; each file contains approximately 520 records per second. The obtained data were filtered in the Comma-separated values CSV file. The data went through a median filter for the eight bands, and the focus was given to the attention of the bands, and those attentions of the bands were received that ranged 70 and above. That is why the bands were used for the classification because that device has separated those features by default.

Table 1. shows all the shapes in different colors that we used in our experiment.

Name of the shapes	Description	Visual content of the shapes
Shape one	Represents a green circle on white background	
Shape two	Represents a blue circle on white background	
Shape three	Represents a red circle on white background	
Shape four	Represents a green rectangle on white background	
Shape five	Represents a blue rectangle on white background	
Shape six	Represents a red rectangle on white background	
Shape seven	Represents a green triangle on white background	
Shape eight	Represents a red (triangle, rectangle, circle) on white background	

6. EXPERIMENTAL RESULTS

After gaining and collecting all the data in a CSV file, a label was given for all the participants for each shape. After preparing the data by the Random Forest algorithm, a needed code was given for implementing the classification of the objects to be in a way to provide the highest accuracy. Random Forest algorithm is used for the classification of 8 cases based on the dataset. This dataset was divided into training and testing parts. Different ratios are used to find out the relationship between vision and the brain wave signals, and the ratios include 1-8, 2-7, 3-6, 4-5, 5-4, 6-3, 7-2, 8-1 for training and testing respectively, as shown in table.2. As shown in Figure 6, The overall accuracy is 20.48%, but it probably achieves a better result using other algorithms and methods. The best result was achieved in case 8, where there were eight pieces of training and one testing, compared to other cases.

Table 2. number of training and testing datasets

#	Number of Cases	Number of Training Samples	Number of Testing Samples
1	Case One	One	Eight
2	Case two	two	seven
3	Case three	three	six
4	Case four	four	five
5	Case five	five	four
6	Case six	six	three
7	Case seven	seven	two
8	Case eight	eight	one

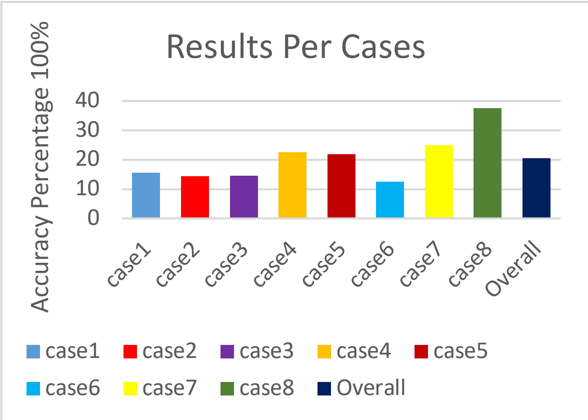

Figure 6. Describes the accuracy of cases in table 2

The obtained results are based on the shapes and colors, i.e., green circle (12.5%), blue circle (16.07%), red circle (6.25%), green rectangle (15%), blue rectangle (15.625%), red rectangle (8.33%), green triangle (25%) and triangle, rectangle and circle all together in red color (37.5%). The results show that, in general, the red color has the greatest influence on the relationship between vision and brain wave signals.

7. CONCLUSION

In this work, an experiment has been made to prove the connection between human vision information and simultaneous brain signal. Brain wave signals are captured in the situation that the participants looking at the specific shape, then the collected signals are organised into training and testing groups, after that Random Forest classifier is used to classify the signals. The accuracy results demonstrate that objects in the scene can be classified based on simultaneous brain signals. Overall accuracy for all shapes as separated as per cases is 20.48%, and shapes numbers 6 and 8 are 55.34% 36.57%, respectively. It can be concluded that human brain signals can be categorised based on human vision inputs.
Additionally, the accuracy percentage can be improved by considering the number of points. First, using more advanced and proper EEG tools is to make the data as clear and receive the signals of the occipital lobe. Second, it includes pre-processing brain signals using signal processing techniques, such as extracting features of the signal by using FFT or DWT methods. Third, different machine learning techniques can be exploited to classify the signals. The fourth was capturing more data which means increasing more participants in the experiment, especially for the training phase.

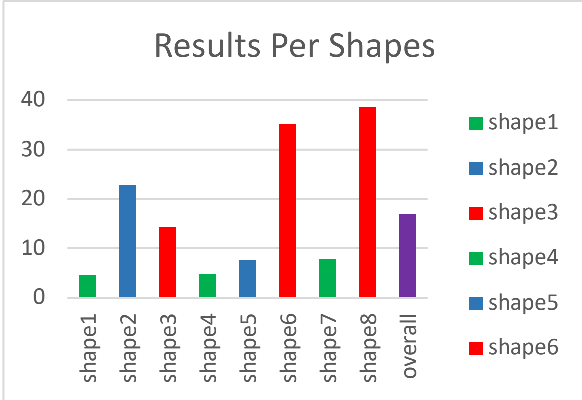

Figure 7. Represents the accuracy results per shapes

REFERENCES

Azar, A. T., Balas, V. E., & Olariu, T. (2014). Preface. *Studies in Computational Intelligence*, *486*, 97–106. doi: 10.1007/978-3-319-00467-9

Barroso, H. (2014). An introduction to human neuroanatomy. *Academia.edu*. Berreskuratua -(e)tik https://www.academia.edu/24696681/An_Introduction_To_Human_Neuroanatomy

Breiman, & L. (2001). *Random Forests*. 5–32.

Chen, M., Cao, Y., Wang, R., Li, Y., Wu, D., & Liu, Z. (2019). DeepFocus: Deep encoding brainwaves and emotions with multi-scenario behavior analytics for human attention enhancement. *IEEE Network*, *33*(6), 70–77. doi: 10.1109/MNET.001.1900054

Dzaferovic, & E. et al. (2017). Cloud-based mobile platform for EEG signal analysis. *International Conference on Electronic Devices, Systems, and Applications*. doi: 10.1109/ICEDSA.2016.7818497

Fiscon, G., Weitschek, E., Cialini, A., Felici, G., Bertolazzi, P., De Salvo, S., Bramanti, A., Bramanti, P., & De Cola, M. C. (2018). Combining EEG signal processing with supervised methods for Alzheimer's patients classification. *BMC Medical Informatics and Decision Making*, *18*(1), 1–10. doi: 10.1186/s12911-018-0613-y

Hima, & C.S. (2015). *World Journal of Pharmaceutical Sciences Psoriasis – An Overview*. *8*(11), 59–66.

Jo, S. Y., & Jeong, J. W. (2020). Prediction of visual memorability with EEG signals: A comparative study. *Sensors (Switzerland)*, *20*(9), 1–19. doi: 10.3390/s20092694

K. Rostam, Z. R., & Mahmood, S. A. (2019). Classification of Brainwave Signals Based on Hybrid Deep Learning and an Evolutionary Algorithm. *Journal of Zankoy Sulaimani - Part A*, *21*(2), 35–44. doi: 10.17656/jzs.10755

Khade, D. A., & Ilakiyaselvan, N. (2017). Scene and object classification using brain waves signal. *Asian Journal of Pharmaceutical and Clinical Research*, *10*, 137–139. doi: 10.22159/ajpcr.2017.v10s1.19495

Khosla, A., Khandnor, P., & Chand, T. (2020). A comparative analysis of signal processing and classification methods for different applications based on EEG signals. *Biocybernetics and Biomedical Engineering*, *40*(2), 649–690. doi: 10.1016/j.bbe.2020.02.002

Kim.H, KOEHLER. GJ, & 1995. (1995). *Theory and Practice of Decision Tree Induction*. *23*(6), 637–652.

Nair, A. V., Kumar, K. M., & Mathew, J. (2018). An Improved Approach for EEG Signal Classification using Autoencoder. *Proceedings of the 2018 8th International Symposium on Embedded Computing and System Design, ISED 2018*, 6–10. doi: 10.1109/ISED.2018.8704011

Onesmus Mbaabu. (2020). *Introduction to Random Forest in Machine Learning*. Berreskuratua -(e)tik https://www.section.io/engineering-education/introduction-to-random-forest-in-machine-learning/

Pal, C. V., & Leon, F. (2020). A Modified I2A Agent for Learning in a Stochastic Environment. In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Libk. 12496 LNAI. doi:

10.1007/978-3-030-63007-2_30

Sałabun, W. (2014). Przetwarzanie i analiza widmowa sygnałów EEG przy zastosowaniu urza{ogonek}dzenia MindWave MW001. *Przeglad Elektrotechniczny*, *90*(2), 169–173. doi: 10.12915/pe.2014.02.44

Siradjuddin, I. A., Septasurya, R., Sophan, M. K., Ifada, N., & Muntasa, A. (2017). Feature selection with Genetic Algorithm for alcoholic detection using electroencephalogram. *Proceedings - 2017 International Conference on Sustainable Information Engineering and Technology, SIET 2017*, *2018-Janua*, 230–234. doi: 10.1109/SIET.2017.8304140

Tajdini, M., Sokolov, V., Kuzminykh, I., Shiaeles, S., & Ghita, B. (2020). Wireless sensors for brain activity—a survey. *Electronics (Switzerland)*, *9*(12), 1–26. doi: 10.3390/electronics9122092

Tonya. (2018). Anatomy of the Brain. *Mayfield Clinic Ohio*.

Ullah, H., Uzair, M., Mahmood, A., Ullah, M., Khan, S. D., & Cheikh, F. A. (2019). Internal Emotion Classification Using EEG Signal with Sparse Discriminative Ensemble. *IEEE Access*, *7*(c), 40144–40153. doi: 10.1109/ACCESS.2019.2904400

Zheng, W. L., Zhu, J. Y., Peng, Y., & Lu, B. L. (2014). EEG-based emotion classification using deep belief networks. *Proceedings - IEEE International Conference on Multimedia and Expo*, *2014-Septe*(Septmber). doi: 10.1109/ICME.2014.6890166

Zhou, J., Wang, G., Liu, J., Wu, D., Xu, W., Wang, Z., Ye, J., Xia, M., Hu, Y., & Tian, Y. (2020). Automatic Sleep Stage Classification with Single Channel EEG Signal Based on Two-Layer Stacked Ensemble Model. *IEEE Access*, *8*, 57283–57297. doi: 10.1109/ACCESS.2020.2982434