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The Classification of Human Emotions Based on The Electroencephalogram (EEG) of Brain Waves

Nabilah Farhana Nordin, Norma Alias
Department of Mathematical Sciences, Faculty of Science
Universiti Teknologi Malaysia, 81310, Johor Bahru, Malaysia

Abstract
The purpose of this study is to investigate the classification of human emotions based on the electroencephalogram (EEG) of brain waves. Brain waves are electrical voltages in the brain that oscillate at only a few millionths of a volta. The five commonly recognized brain waves are $\alpha, \beta, \gamma, \theta$ and δ. Each of these waves has its unique frequencies and the features of brain states. Since human emotion is completely complex and different from each other, the approaches and methods for identifying the brain wave are not accurate and applicable. It also must be admitted that this kind of research is still in its initial phase of evolution. Other than that, the classification was done without any help from an expert that works in the medical line. This research focuses on the emotions and character of the individual that can be studied by using the EEG of brain waves. Data was collected by profile women whose studies and working in UTM. Then, the data will be analyzed in Scilab by using Discrete Fourier Transform (FFT) to attract all brain waves in the txt file. Furthermore, image screen processing by CNN, brainwave training model, and prediction of brain waves will be performed by python programming integrated with Spyder and Jupyter. Moreover, the data of prediction brain waves were presented in Excel. The brain activity such as listening, watching, talking and brainstorming during the time EEG readings is taken, the result expectations of the brain waves are low frequency in delta, theta, and alpha brainwave and high in beta and gamma brainwaves. The classifications are using fuzzy logic (If not A, then B). For this case, it is either high activity and amplitude or low activity and amplitude. There is no middle ground, so normal activity and amplitude are considered low activity and amplitude categories. As a result, studies on the relationship between how a person's emotions can relate to their brainwaves can be carried out. The person with low in delta waves shows that she maybe has difficulty focusing. Excesses theta waves during conscious appear that the person was distracted and disorganized. Normal alpha waves appear when the person is calm and relaxed. The high beta will shows that the person is a busy thinker and high gamma waves reveal that the person doing some high-level information processing. This study reviews the method of analyzing the EEG of brain waves and the technique to extract the features of the brain wave accurately. Future research must focus on the detailed emotion classification as the research done to date is only rough emotion classification.
Keywords Brain waves, Electroencephalogram, Discrete Fourier Transform, CNN

1. Introduction

Brain waves are electrical voltages in the brain that oscillate at only a few millionths of a volt. The five commonly recognised brain waves are alpha, gamma, betta, theta, and delta, and each of these waves has its unique frequencies of human EEG waves as well as features of brain states [1]. Alpha waves, for example, have a frequency of 8-12 Hz and are associated with a peaceful and passive state of mind. Delta waves, which have a frequency of 0.5-4 Hz and occur during sleep. Gamma, Beta, and Theta have EEG waves with frequencies of 35 Hz, 12-35 Hz, and 4-8 Hz, respectively [2].

The gamma wave is the fastest type of brain activity. Cognitive functioning, learning, memory, and information processing are all controlled by it. When this wave is prominent, it causes anxiety, high arousal, and stress, whereas when it is suppressed, it causes attention deficit hyperactivity disorder

(ADHD), depression, and learning difficulties. Gamma waves aid attention, focus, sensory binding, consciousness, mental processing, and perception in ideal conditions.

Next, beta waves are high-frequency, low-amplitude brain waves that can be seen when you're awake. They stimulate conscious thought and logical thinking. We can focus if we have the correct amount of beta waves. When this wave is prominent, it generates anxiety, high arousal, inability to relax, and tension, and when it is suppressed, it can induce ADHD, daydreaming, sadness, and poor cognition [3]. Beta waves aid conscious focus, memory, and problem solving when conditions are ideal.

Furthermore, the frequency range of alpha waves is between beta and theta. Alpha waves assist us in de-stressing and promoting sensations of profound relaxation when needed. Daydreaming, difficulty to focus, and being excessively relaxed are all examples of Alpha waves. Anxiety, increased tension, and insomnia can result if they are suppressed. It leads to a relaxed mood when they are at their best. Then, day dreaming and sleep are both influenced by the Theta wave frequency range. When theta waves are prominent, it is associated with ADHD, depression, hyperactivity, impulsivity, and inattentiveness and when they are suppressed, it is associated with anxiety, poor emotional awareness, and stress. Theta assists with creativity, emotional connection, intuition, and relaxation when it is in its ideal state [4].

Moreover, Delta waves are the slowest brain waves ever recorded in humans. They're most common in babies and small children, and they're linked to the deepest levels of relaxation and restorative, healing sleep. Brain damage, learning issues, inability to think, and severe ADHD are all common symptoms of Delta. If this wave is inhibited, it prevents the body from rejuvenating and the brain from rejuvenating, as well as bad sleep. The immune system, natural healing, and restorative/deep sleep are all aided by sufficient generation of delta waves [5].

According to brain science, human emotions are governed by the brain. As it transmits messages, the brain generates brain waves. Brain wave data is one type of biological message, and is often associated with emotion. The features of emotion can be retrieved from brain wave transmissions by analysing them. However, the complexity of human emotion is generated by the environmental background and cultural diversity of human development. As a result, the classification method is critical in the analysis of brainwave emotion.

The emotions and character of the individual can be studied by using the EEG of brain wave [6]. Hence, to carry out this project we collected data from the EEG of brain wave of women who work and study at UTM. Then, from the data EEG signal processing will be done by using signal-processing method known as Fast-Fourier Transform Analysis. Classification and analysing of EEG signals is done by using CNN (convolutional neural network model), which is a deep learning model. It consists of testing and interpretation to classify brain wave and to identify the symptoms [7].

2. Literature Review

2.1. EEG

2.1.1. Electroencephalography (EEG)

Electroencephalography, or EEG, is one of the medical procedures. The most widely used instrument for studying brain function is the electroencephalogram (EEG). The EEG is used to detect brain problems [8]. Moreover, the EEG curve (Electroencephalogram) is a representation of brain activity as a change in time of electric capability (EEG signal) [9]. Everyone's signal is different, and it fluctuates according to age, gender, awareness, and other characteristics. For similar types of human activities, the signal's character is largely identical. As a result, the signal is worth evaluating.

2.1.2 EEG-based emotion recognition

Emotion recognition is now done in two ways: non-physiological cues or physiological signals [10]. Text, voice, facial emotions, and gestures are examples of non-physiological approaches. However, because facial gestures or voice tone might be obfuscated voluntarily, this method cannot be regarded as dependable [11]. Unlike the first, the second technique, which uses physiological signals, appears to be more efficient and dependable because physiological signals cannot be controlled purposefully. Emotion detection utilizing the EEG signal has become the most preferred non-invasive method among all available physiological signals, as EEG efficiently records the electrical activity of the brain [12]. EEG-based approaches have become more feasible with the development of sensor networks, intelligent sensing systems, and energy-efficient biomedical equipment

2.1.2. Human emotions

Happiness, anger, fear, surprise, sadness, and disgust are six basic emotions that can be classified into six groups [13]. The following are some psychologists' perspectives on basic emotions. First, fear is the innate reaction of a common species or person when confronted with a life-threatening situation [14]. Changes in heart rate, blood pressure, night sweats, tremors, and other physiological phenomena, as well as the signs of cardiac arrest shock, can all be caused by fear. Secondly, anger is a strong emotion that many people experience [15]. Emotional stress, as well as being violated, mistreated, or treated unfairly, might trigger an innate self-defence response. Emotional rage, micro lukewarmness, resentment, inequity, impatience, hostility, and, to a greater extent, hatred and violence. Thirdly, sadness is frequently a psychological reaction to failure, and the mood has a negative connotation [16]. Sadness, depression, self-pity, loneliness, depression, despair, and morbid severe melancholy are all emotions. Fourth, joy is a psychological state of pleasure that includes feelings of happiness, contentment, self-satisfaction, pride, and excitement [17]. Fifth, a surprise is an unexpected stimulus in the living environment that prompts a temporary response to stop it [18]. Lastly, disgust is an emotion when being exposed to unpleasant sensations in the surroundings.

2.1.3. Introduction to the brain wave

There are five types of brain waves in which every wave has their physiological state which are Delta, Theta, Alpha, Beta and Gamma [19]. Delta waves are the most critical brain waves in new-born and frequently arise during deep sleep-in adults [20]. This wave is frequently used as the foundation for sleep therapy, which measures the amount of energy released by the patient's Delta wave and evaluates whether or not the patient has entered a deep sleep state. Delta waves are required for physical sleep recovery. Next, Theta is a type of brain wave that manifests in a shallow sleep state, often known as a meditative state, and refers to the brain waves that occur when people initially fall asleep [21]. Because the brain functions as a memory and behaviour is trained as an unconscious action, theta waves are higher when we do memory, perceptual, and emotional linked behaviours. Furthermore, the predominant brain wave in normal, relaxed individuals is the alpha wave [22]. The state of consciousness progressively shifts from clarity to ambiguity. It's also about unwinding and freedom. The alpha wave is linked to brain activity, and when the energy released by the Alpha Wave is high, it reflects the brain wave in the greatest learning and thinking condition. Moreover, Beta waves are related to concentration, and higher-energy beta waves indicate a positive increase in attention [23]. Lastly, the Gamma wave is linked to happiness [24]. When the Gamma Wave's energy is higher, it indicates a greater sensation of enjoyment. This wave is linked to stress reduction. The greater the energy released by the Gamma wave, the greater the pressure released [25].

2.1.4. Linear classifier

To produce classification judgments, linear classifiers use a linear combination of features [26]. From the viewpoint of a two-dimensional space. If the feature of the two categories is to be classified. A straight line is a linear classifier. This line can result in two different types of points. The expression is defined as $y = ax + b$. Linear regression, linear discriminant analysis (LDA), linear support vector machine, single-layer Perceptron network, and basic Bayesian classifier (Naive Bayes) are all examples of linear classifiers [27]. Linear regression models especially were used in the off-line data analysis to extract EEG features.

2.1.5. Continuous wavelet transforms (CWT)

In many sectors of science and engineering, the continuous wavelet transform (CWT) has played an important role in the analysis of time-frequency data. It is based on the short-time Fourier transform, but with variable time-frequency resolution [28]. The Fourier Transform is a handy tool for analyzing the signal's frequency component. Mao, W.L (2020) said that the Short-time Fourier Transform (STFT) uses a sliding window to find a spectrogram, which contains both time and frequency information.

2.1.6 Convolutional neural network (CNN)

Convolutional Neural Networks, or CNNs, have become a popular deep neural network method in recent years [29]. Mao, W.L (2020) studied said CNNs are image processing, artificial intelligence (AI) systems that employ deep learning to do both generative and descriptive tasks, frequently using machine vision that includes image and video recognition, recommender systems, and natural language processing (NLP), Convolutional layer, Relu layer, Pooling layer, and fully connected layer are the four key features layers in CNN).

2.1.7 Fast Fourier Transform (FFT)

For data with 1000 observations, the Fast Fourier Transform method requires around 10,000 mathematical algorithm operations, which is 100 times faster than the previous method. With the discovery of the Fast Fourier Transform and the development of personal computers, the Fast Fourier Transform technique in data analysis became popular and is now one of the standard methods [30]. The Fourier transform is a type of transformation that is commonly used to convert signals from the time domain to the frequency domain [31].

3. **Methodology**

3.1. Research Data

The purpose was to profile women to classify the human emotions based on the electroencephalography (EEG) of brain waves at the Universiti Teknologi Malaysia, Skudai, Johor Bahru around December 2021 between 9:00 am until 6:00 pm. The volunteer for this research were those over 18 years old who were living, studying and working in the area of Universiti Teknologi Malaysia, Skudai, Johor Bahru. These respondents were selected around the UTM area because of their psychological well-being based on their emotions and behaviours. The process does not take too long and only takes about 15 minutes per person. The volunteers are required to watch seven videos that have been prepared including sad, happy and scary videos using a customized cyberphysical device. Furthermore, the mathematical methods for extracting features from EEG signals that used for this research is Discrete Fourier transform (FFT) that used to attract brain waves. Gao (2020) said that classification and analyzing the EEG signals is done by using CNN (convolutional neural network model), which is a deep learning model.

3.2. Fast Fourier Transform (FFT)

Fast Fourier Transform (FFT) is use to attract all brain wave in txt file. Scilab programming is used in this analysis. It is the algorithm that transforms the time domain signals to the frequency domain components [32]. This method analyses EEG data using mathematical means or tools and crucial and efficient tool for the feature extraction. The FFT technique involves a variety of mathematical operations, ranging from simple real and complex number arithmetic through group theory and number theory. The result of the FFT can be computed using the O (N log N) operation. N denotes the vector's length.

3.3. Brainwave reconstruction

The following stages, brainwave reconstruction will be performed. Python programming are used for these stages integrated using Spyder. The data obtained from the previous stages which is the FFT

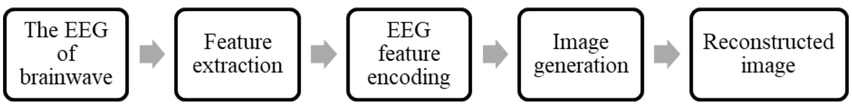


Figure 1 The algorithm of brainwave reconstruction

result will be use in the reconstruction brainwaves. Figure 1 show the algorithm for the brainwave reconstruction.

3.4. Image screen processing

Moreover, the next stage is image screen processing. This stage was performed using python programming integrated by Jupyter Notebook. The image screen processing is usually performed before CNN model will be created. Furthermore, during this stage, the image of brainwave will be converted into number data set. Image processing is a technique for applying operations on an image in order to improve it or extract relevant information from it. It's a sort of signal processing in which the input is an image and the output is either that image or its characteristics/features [33]. In this process the image of the brainwave will be converted to square since it is the best input to use CNN. Also, the data image transformed to grayscale to avoid high processing power. Next, creating training data using *class_num* (0-normal, 1-high). The data will be saved and shuffle to avoid the programming learn the pattern of data. Finally, the data will be saved into one directory which is pickle, the number data set using in Python.

3.5. CNN model

For the further step, CNN model will be created and train. The objective for this training is to minimize the error and also improve the data accuracy. There is the step used to training the CNN including upload dataset, the input layer, convolutional layer, pooling layer also convolutional layer and pooling layer. Figure 3.2 show the algorithm of CNN for EGG spectrogram classification. Besides, after trained the CNN model, the data brain waves will be predicted and characterizes between high or normal waves.

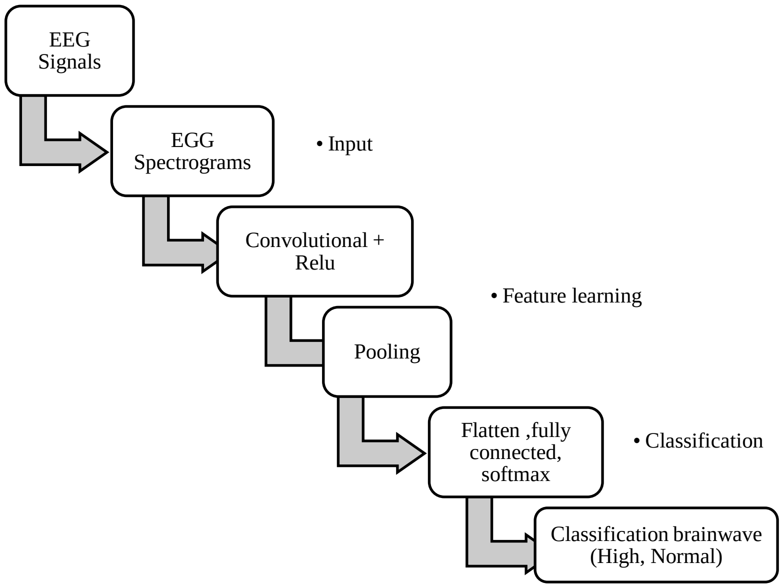


Figure 2 The algorithm of CNN for EGG spectrogram classification

4. Results and discussion

4.1. Fast Fourier transform (FFT)

The FFT was apply all the brain wave into txt files. Total of six videos for the EEG of brain waves were analyzed using Scilab as a programming software. The results shown in the table below are the results of all the respondents' data using FFT for video 1. Since the result of the FFT data is too big, only the data from time 0 to 0.008 seconds of video 1 are shown below.

Table 1 FFT results for Video 1

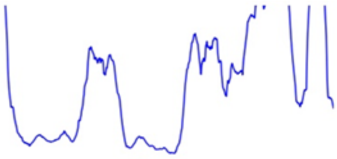
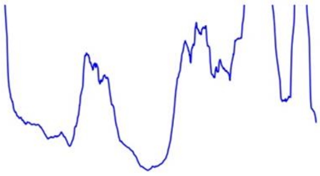
Respondents	Time (s)	Delta	Theta	Alpha	Beta	Gamma
Sample 1	0	2.781533639131767E-006	9.157284854177837E-007	1.027987575358381E-006	1.506948104274528E-006	1.285045270664540E-006
	0.004	5.517081791554981E-006	1.808455822214256E-006	2.072410786735422E-006	2.986809287620937E-006	2.574080114961465E-006
	0.008	8.188959718631228E-006	2.666925884749692E-006	3.159082022193046E-006	4.513776786107681E-006	3.958545463744504E-006
Sample 2	0	2.076372942372615E-006	1.269525435097909E-006	6.846633587916079E-007	1.372329054155108E-006	6.414080676235439E-007
	0.004	4.184140710480961E-006	2.528614510690850E-006	1.344899461571241E-006	2.834844776752389E-006	1.273775291924796E-006
	0.008	6.335999622041435E-006	3.766780747070654E-006	2.001209560837844E-006	4.286521366633866E-006	1.887947220028380E-006
Sample 3	0	1.300200725718198E-006	6.087261643318494E-007	9.047089933735695E-007	1.533163351267778E-006	1.423138015066938E-006
	0.004	2.600942108522306E-006	1.231093538544775E-006	1.784823644119823E-006	3.035986144184755E-006	2.812636717001654E-006
	0.008	3.901714511220551E-006	1.858122063130209E-006	2.651720459967959E-006	4.520873068845655E-006	4.175970936950387E-006
Sample 4	0	3.343803914866140E-006	6.353714332907988E-007	7.613916895249641E-007	9.858872885555543E-007	9.335228899523625E-007
	0.004	6.702779062409279E-006	1.247410137920483E-006	1.539300247063679E-006	2.071935490536753E-006	1.812684308935578E-006
	0.008	1.007810016675564E-005	1.833386805939017E-006	2.317282923389106E-006	3.252759946375111E-006	2.694465940178177E-006

4.2. Brainwave reconstruction

The data from the FFT will be adopted for the brainwave reconstruction. For these stages, Spyder will be used which is the open-source scientific environment written in Python. By analyzing and reconstructed the brain wave, it will show the brain wave patterns are distinct for each category of videos. Hence, this implements the analyzation of the brain's response to videos in real-time. This information is important to do the CNN model since this model are suitable for data image rather than data time. Table below show the image of brainwave reconstruction for delta, theta, alpha, beta and gamma that was sort into two categories which are a bit high and seems normal.

Table 2 The image of brainwave reconstruction

Brainwave	A bit high	Seems normal
Alpha		

Beta		
Gamma		
Theta		
Delta		

4.3. Convolutional neural network (CNN)

The CNN model of the EEG of brainwave will be trained and predict using python programming (Jupyter). This CNN model consists of 10 layers involving two conventional layer, three activation (Relu) layer, two max pooling layers, one flattens and two dense. Table 3 show summary for the model parameter values for the training model CNN. The first convolutional layer filters the (198 x 198 x 64) input image. The second convolutional layer take the output of the first convolutional layer and filter with (97 x 97 x 64). Since the final pooling and convolutional layer gives a three-dimensional matrix as output to flatten the matrix. A flattening layer are adopted which converts into a vector then, be the input for one dense.

Table 3 Model parameter values

Layer (type)	Output Shape	Parameter
conv (Conv2D)	(None, 198, 198, 64)	640
activation (Activation)	(None, 198, 198, 64)	0
max_pooling2d (MaxPolling2D)	(None, 99, 99, 64)	0
conv2d_1 (Conv2D)	(None, 97, 97, 64)	36928

activation_1 (Activation)	(None, 97, 97, 64)	0
max_pooling2d_1 (MaxPolling2D)	(None, 48, 48, 64)	0
flatten (Flatten)	(None, 147456)	0
dense (Dense)	(None, 64)	9437248
dense_1 (Dense)	(None, 1)	65
activation_2 (Activation	(None,1)	0
Total parameter: 9 474 881 Trainable parameters: 9 474 881		

The whole CNN model will be compiling and used loss function which is binary cross entropy to the model. The binary is adopted to characterize two types of decisions such as 0 for normal and 1 for high. For the optimizer, *adam* will be used and accuracy as a metrices to track performance based on the accuracy. Furthermore, the training model used four batch size to train in one time, 15 epochs and 20% validation split. Subsequently, the CNN model of training data will be predicted in Jupyter Notebook. The brainwave was sort off into two categories which is a bit high and seems normal. The table below show the result after the prediction of brain wave for all the respondents which is the percentage overall brain activity.

Table 4 Sample 1 overall brain activity (%)

Activity	Alpha	Delta	Theta	Gamma	Beta
A bit high	47.37	83.33	52.63	94.44	89.47
Seems normal	52.63	16.67	47.37	5.56	10.53

For the first sample, has a high Delta wave, indicating that she is awake and possibly having difficulty concentrating. Theta waves appear when people are awake, and this respondent's percentage of this wave is 52.6%, indicating that she is preoccupied or disorganized. With 53% Alpha waves, this respondent was similarly quite calm and comfortable. Then, the presence of a large percentage of the Beta wave indicates that the respondent is an actively busy thinker. Finally, sample 1 Gamma wave is quite high, indicating that she is engaged in integrated thinking or high-level information processing.

Table 5 Sample 2 overall brain activity (%)

Activity	Alpha	Delta	Theta	Gamma	Beta
A bit high	94.74	83.33	94.74	33.33	47.37
Seems normal	5.26	16.67	5.26	66.67	52.63

For the second sample, has a high Delta wave, indicating that she is awake and maybe having difficulties focusing on things. Next, this respondent has higher Theta waves probably because she is distracted, disorganized and impulsively. Excessive Alpha waves in these respondents could mean that she has ADHD (Attention-Deficit/Hyperactivity Disorder) or is depressed. The presence of 47% Beta waves suggests that sample 2 is a busy thinker who may also suffer from a lack of attention. Finally, 30% of sample 2 Gamma wave is involved in integrated thinking or may have a learning problem.

Table 6 Sample 3 overall brain activity (%)

Activity	Alpha	Delta	Theta	Gamma	Beta
A bit high	21.05	16.67	21.05	94.44	94.74
Seems normal	78.95	83.33	78.95	5.56	5.26

The Delta waves for the third sample, are fairly low, indicating that she is unlikely to have trouble concentrating. Furthermore, sample 3 Theta wave percentage is 21, indicating that she has a high level of focus most of the time. These respondents are also in a tranquil frame of mind the majority of the time, as seen by her low Alpha wave proportion. The Beta wave proportion was then at 94%, showing that she was a very engaged thinker. Finally, the high Gamma waves in sample 3 signal that she is thinking or performing high-level information processing.

Table 7 Sample 4 overall brain activity (%)

Activity	Alpha	Delta	Theta	Gamma	Beta
A bit high	26.32	16.67	31.58	16.67	21.05
Seems normal	73.68	83.33	68.42	83.33	78.95

For the fourth respondent, sample 4 is unlikely to have difficulty focusing because her Delta waves are quite low in percentage. Furthermore, because the Theta wave is prevalent while awake, sample 4 may be easily distracted or disorganized, as the wave is present 52.63% of the time. Furthermore, she is in a peaceful state of mind, and her Alpha wave is relatively low, indicating that she is thinking. Furthermore, the Beta wave was low, indicating that she is either relaxed yet focused or that she lacks concentration most of the time. Finally, sample 4 Gamma waves were 16%, indicating that she was not engaged in integrated thought or hindered mental processing.

Based on the analyzing data, we can classify the sample based on their emotion. Table 8 shown the frequencies for each brain waves whether its stable or unstable state of emotion. For stable emotion, the alpha, delta and theta must in low frequency while gamma and beta in high frequency. Meanwhile, for unstable state of emotion the alpha, delta and theta are in high frequency while gamma and beta in low frequency. Next, sample 1 until 4 can be classify in two categories which is emotion stable and emotion unstable based on the table 9.

Table 8 State of emotion based on frequency of brain waves

	Alpha	Delta	Theta	Gamma	Beta
Stable	Low	Low	Low	High	High
Unstable	High	High	High	Low	Low

Table 9 Categories of emotions

Emotion stable	Emotion unstable
Sample 1	Sample 2
Sample 3	Sample 4

5. Conclusion

In this research paper, particularly to investigate the classification of human emotions based on the electroencephalogram (EEG) of brain waves. Emotions can represent mental health by using brain physiological data such as the EEG. Using the FFT and CNN model the EEG of brain waves can be analyzed. Next, the data will be predicted and the emotion can be distinguished from the EEG of the brain wave. All the brain waves alpha, beta, gamma, theta and delta can be analyzed to distinguish and classify the emotion of humans. For this research, we can conclude sample 1 and 3 have stable emotion while sample 2 and 4 have unstable emotion. Moreover, a full overview study of EEG of brain waves has been conducted using AI, and deep machine learning including python and CNN. Data acquisition techniques, control signals, EEG feature extraction, classification methods, and performance evaluation measures are investigated for each BCI application. Finally, potential issues with EEG-based BCI devices were discussed, and interesting alternative options were suggested. To conclude, much research and innovation are needed to identify more accurate techniques to extract the features of the brain wave.

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References

[1] Abhang, P. A., Gawali, B., & Mehrotra, S. C. (2016). Introduction to EEG-and speech-based emotion recognition. Academic Press.

[2] Ali, A., Afridi, R., Soomro, T. A., Khan, S. A., Khan, M. Y. A., & Chowdhry, B. S. (2022). A Single-Channel Wireless EEG Headset Enabled Neural Activities Analysis for Mental Healthcare Applications. Wireless Personal Communications, 1-15.

[3] Marzbani, H., Marateb, H. R., & Mansourian, M. (2016). Neurofeedback: a comprehensive review on system design, methodology and clinical applications. Basic and clinical neuroscience, 7(2), 143.

[4] Koudelková, Z., & Strmiska, M. (2018). Introduction to the identification of brain waves based on their frequency. In MATEC Web of Conferences. EDP Sciences.

[5] Gao, D., Long, S., Yang, H., Cheng, Y., Guo, S., Yu, Y., ... & Yao, D. (2020). SWS brain-wave music may improve the quality of sleep: an EEG study. Frontiers in neuroscience, 14, 67.

[6] Hamada, M., Zaidan, B. B., & Zaidan, A. A. (2018). A systematic review for human EEG brain signals based emotion classification, feature extraction, brain condition, group comparison. Journal of medical systems, 42(9), 1-25.

[7] Tajbakhsh, N., Shin, J. Y., Gurudu, S. R., Hurst, R. T., Kendall, C. B., Gotway, M. B., & Liang, J. (2016). Convolutional neural networks for medical image analysis: Full training or fine tuning? IEEE transactions on medical imaging, 35(5), 1299-1312.

[8] Mao, W. L., Fathurrahman, H. I. K., Lee, Y., & Chang, T. W. (2020). EEG dataset classification using CNN method. In Journal of physics: conference series (Vol. 1456, No. 1, p. 012017). IOP Publishing.

[9] Strmiska, M., & Koudelkova, Z. (2019). Analysing EEG signals for mathematical computations. In MATEC Web of Conferences (Vol. 292, p. 01043). EDP Sciences.

[10] Ali, M., Mosa, A. H., Machot, F. A., & Kyamakya, K. (2018). Emotion recognition involving physiological and speech signals: A comprehensive review. Recent advances in nonlinear dynamics and synchronization, 287-302.

[11] Patel, P., & Annavarapu, R. N. (2021). EEG-based human emotion recognition using entropy as a feature extraction measure. Brain Informatics, 8(1), 1-13.

[12] Houssein, E. H., Hammad, A., & Ali, A. A. (2022). Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review. Neural Computing and Applications, 1-31.

[13] Eimer, M., Holmes, A., & McGlone, F. P. (2003). The role of spatial attention in the processing of facial expression: an ERP study of rapid brain responses to six basic emotions. Cognitive, affective, & behavioral neuroscience, 3(2), 97-110.

[14] Kish-Gephart, J. J., Detert, J. R., Treviño, L. K., & Edmondson, A. C. (2009). Silenced by fear:: The nature, sources, and consequences of fear at work. Research in organizational behavior, 29, 163-193.

[15] Parkinson, B. (2019). Emotion. In Companion encyclopedia of psychology (pp. 485-505). Routledge.

[16] Domínguez-Jiménez, J. A., Campo-Landines, K. C., Martínez-Santos, J. C., Delahoz, E. J., & Contreras-Ortiz, S. H. (2020). A machine learning model for emotion recognition from physiological signals. Biomedical signal processing and control, 55, 101646.

[17] Desmet, P. M. (2012). Faces of product pleasure: 25 positive emotions in human-product interactions. International Journal of Design, 6(2).

[18] Barrett, L. F. (2017). How emotions are made: The secret life of the brain. Pan Macmillan.

[19] Wang, Y., Wang, S., & Xu, M. (2022). Landscape Perception Identification and Classification Based on Electroencephalogram (EEG) Features. International journal of environmental research and public health, 19(2), 629.

[29] Hamood, M. H. (2021). Understanding of Sleep and Importance of its Stages (Doctoral dissertation, University of Diyala).

[21] Paszkiel, S. (2020). Analysis and classification of EEG signals for brain-computer interfaces (pp. 11-17). Cham: Springer International Publishing.

[22] Tantra, J., Juan, S. I., Tsaih, L. S., & Chiang, W. H. (2022). Relaxation response with gentle stream sound: A study using brainwave. The Journal of the Acoustical Society of America, 151(4), A72-A72.

[23] Nargundkar, S., Manage, P., & Desai, V. (2020, October). A Survey on Effects of Various Meditation Interventions on Overall Performance of College Students. In 2020 IEEE Bangalore Humanitarian Technology Conference (B-HTC) (pp. 1-6). IEEE.

[24] Yang, K., Tong, L., Shu, J., Zhuang, N., Yan, B., & Zeng, Y. (2020). High gamma band EEG closely related to emotion: evidence from functional network. Frontiers in human neuroscience, 14, 89.

[25] Li, M. A., Han, J. F., & Yang, J. F. (2021). Automatic feature extraction and fusion recognition of motor imagery EEG using multilevel multiscale CNN. Medical & Biological Engineering & Computing, 59(10), 2037-2050.

[26] Rafi, T. H., Farhan, F., Hoque, M. Z., & Quayyum, F. M. (2020). Electroencephalogram (EEG) brainwave signal-based emotion recognition using extreme gradient boosting algorithm. Annals of Engineering, 1(2), 1-19.

[27] Li, T. M., Chao, H. C., & Zhang, J. (2019). Emotion classification based on brain wave: a survey. Human-centric Computing and Information Sciences, 9(1), 1-17.

[28] Shakshi, R. J. (2016). Brain wave classification and feature extraction of EEG signal by using FFT on lab view. *Int. Res. J. Eng. Technol*, *3*, 1208-1212.

[29] Kalash, M., Rochan, M., Mohammed, N., Bruce, N. D., Wang, Y., & Iqbal, F. (2018, February). Malware classification with deep convolutional neural networks. In 2018 9th IFIP international conference on new technologies, mobility and security (NTMS) (pp. 1-5). IEEE.

[30] Yudhana, A., Mukhopadhyay, S., Karas, I. R., Azhari, A., Mardhia, M. M., Akbar, S. A., ... & Ammatulloh, F. I. (2019, October). Recognizing human emotion patterns by applying Fast Fourier Transform based on brainwave features. In *2019 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)* (pp. 249-254). IEEE.

[31] FADHIL, A. (2018). Performance analysis of hashing mathods on the employment of app. *International Journal of Electrical and Computer Engineering (IJECE)*, *8*(5), 3512-3522.

[32] Mateo, C., & Talavera, J. A. (2018). Short-time Fourier transform with the window size fixed in the frequency domain. Digital Signal Processing, 77, 13-21.

[33] Naresh, K. B. (2018). Image Classification.