EARLY DETECTION on LEARNING DISABILITY CHILDREN by USING EEG SIGNALS

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Abstract— The number of learning disabilities (LD) children has been increased in Malaysia throughout the year. The assessment that available for LD diagnosis is very limited since it involves expert to diagnose the disease. The assessment of LD by using neurophysiological signals has been found as scarce particularly in Malaysia. Thus, this research study has been engineered using EEG signals to early detect if the subjects are having any kind of learning disabilities like autism, attention deficit/hyperactivity disorder (ADHD), dyslexia and to use affective computing to do the identification of learning disability. The brain signal was collected from the subjects aged from 4 to 5 years using a 19 channel EEG machine called the DABO machine. Objective of this research is to focus on early detection if the subjects are having any kind of learning disabilities like autism, attention deficit/hyperactivity disorder (ADHD) or dyslexia by analysing their emotion patterns and to use effective computing to do the identification of learning disabilities. In addition, the aim also demands to note the difference in emotion levels between the subject and the normal group. As far as the methodology of this research is concerned, we center around five distinct states to finish the experiment. These states are the collection of EEG data (raw Data), data pre-processing (filter noise), features extraction which will be analysed using Mel Frequency Cepstral Coefficients or MFCC, classification which will be classified using multilayer perceptron or MLP and lastly the final result. Result shows that there is significant different emotion appear between normal subject and subject with LD. This will benefit the caregiver or parents and also researcher to identify the condition of the children through this early detection.

Keywords— Electroencephalography (EEG), learning disability children, MFCC, MLP.

I. INTRODUCTION

There are many children who suffers through learning disability and whose parents are not aware of their children's emotional behaviours at the time of teaching them something, which could harm them more in the future for not taking care properly. Finding scalable biomarkers for early diagnosis of learning disability is complicated because of the heterogeneity [5] in the appearance of the condition and the need for easy measurements that could be applied consistently during well-baby check-ups. Thus, in this research study, we focus on early detection if the subjects are having any kind of learning disabilities like autism, attention deficit/hyperactivity disorder (ADHD), dyslexia. Then, we use effective computing to do the identification of learning disabilities and finally identify the difference in emotion level between the subject and the normal group.

This research has the potential to contribute in the future research to make early detection of learning disabilities and will help the primary schools all over the world to do the pre-screening. So, before enrolling a new student, it can be ensured that they have no learning disability problems.

II. PREVIOUS WORKS REVIEW

Firstly, EEG is a low-cost [6], easy-to-use brain measurement technology that is being investigated as a potential treatment tool for monitoring abnormal brain growth. For our project, we will check the eeg signals of several subjects and normal kids on different occasions and make a comparison. Rivera et. al. (2021) did something similar. They've diagnosed nine mental disorders with DL. The predominant disorder found was epilepsy, representing 47.83% of the total of studies, followed by depression with 15.22% and schizophrenia with 8.7%. The next disorders correspond to sleep disorder, dementia, and ADHD with a 6.52% for each one, Coma with 4.35%. They used Spatial features from the input data and used ML classification methods like Neural Networks (NNs) and DL (Deep learning) methods like Multilayer Perceptron (MLP), convolutional neural networks (CNN), Recurrent Neural Networks (RNN), Auto-encoders (AE) etc [1, 2, 4, 7]. Similarly, deep neural networks combined with 3D kernels may develop an effective seizure detection system by providing a novel technique to concurrently learn patterns from multi-channel EEG inputs using CNN as in [8].

Secondly, we have used feature extraction (MFCC) to conduct our project, because MFCC traits that are more bio-derived [9]. The human brain is the most complex biological structure known to date, with an estimated 86 billion neurons [10]. EEG signal properties may be extracted using chaos theory and nonlinear dynamic approaches for computer-aided diagnosis [11]. Similarly, Abdolzadegan et al. (2020) used feature selection of linear and nonlinear features like Power Spectrum, Wavelet Transform, Fast Fourier Transform (FFT), Fractal Dimension, Correlation Dimension, Lyapunov Exponent, Entropy, Detrended Fluctuation Analysis and Synchronization Likelihood. The classification accuracy of the approach using SVM is 90.57% while for KNN it is 72.77%. Moreover, the sensitivity of the proposed method is 99.91% for SVM and 91.96% for KNN [12].

Thirdly, our research project requires Multilayer Perceptron (MLP) and Russel's model for execution. The research conducted by Güven et al. (2019) using MLP classifiers gave 82.6% sensitivity and 81.81% accuracy on EEG systems [13]. EEG is frequently utilised because of its great temporal resolution, non-invasiveness, usability, and minimal set-up expenses [14]. Whereas Pham et. al. used nonlinear features, Locality sensitive discriminant analysis, T-test, Classifiers, 10- fold validation. Textural features are widely used in image analyses. The PNN classifier achieved the highest accuracy, sensitivity, specificity, and positive predictive values of 98.70%, 100%, 97.30%, 97.56%, respectively, besting other classifiers [15]. Hui et. al. also used Nonlinear features, Sequential forward selection, K-fold validation. They've used Kernel estimation: k- nearest neighbor as classification method. The highest accuracy of 97.88% was achieved with the KNearest Neighbor (KNN) classifier. The proposed system was developed using a tenfold validation strategy on EEG data from 123 children [16].

III. METHODOLOGY

A. *Collection and Experimental Design*

As far as the collection of the data is concerned, we did collect data of 8 subjects aged 4 to 7 years who are autistic and 2 subjects who are normal. According to 19 brain signal channels, we place the EEG electrode on each subject's head. We tried this experiment on both normal and autistic subjects to meet our requirements in further steps ahead. The electrode is put by the assistance of medical officers in charge at Minds Lab, Penawar Special Learning Center, Taman Melawati, Kuala Lumpur, without having to have a special cover, connecting the electrode directly to the subject's head

The methodology of this study can be conceptualized in the in the diagram stated below:

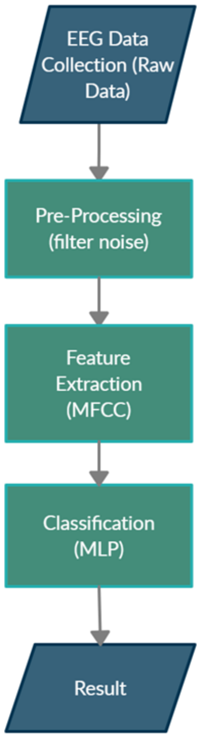

Fig. 1 Methodology Diagram

We go on to the next phase of the test to record the brain signal if the subject's eyes are opened and closed within 60 seconds (1 minute). The experiment continues by viewing 60 seconds of joyful, calm, sad and scared movies in the IAPS (International Affective Picture System) Emotional Sequence [17] and capturing the brain signal displayed throughout the whole video. As recording SAM score might be a bit difficult due to the subjects' age, we used the clenching hands process where the subjects follow a video on clenching hand movements which continues for straight 60 seconds (1 minute). This type of task can help identify a child with autism as they are resistant to their fine motor movements. Then, we continue to the next phase where we deal with the memory test of the subjects. In this case, we use a game called "Matching Game" that requires the subject to memorize the picture first and then the picture will be closed. After that, they will have to match the same picture based on their memory. This process takes 120 seconds (2minutes).

In the end, before we finish our experiment, during a 60 second timespan, we perform and record the brain signal of the subject while having their eyes opened and closed again [18].

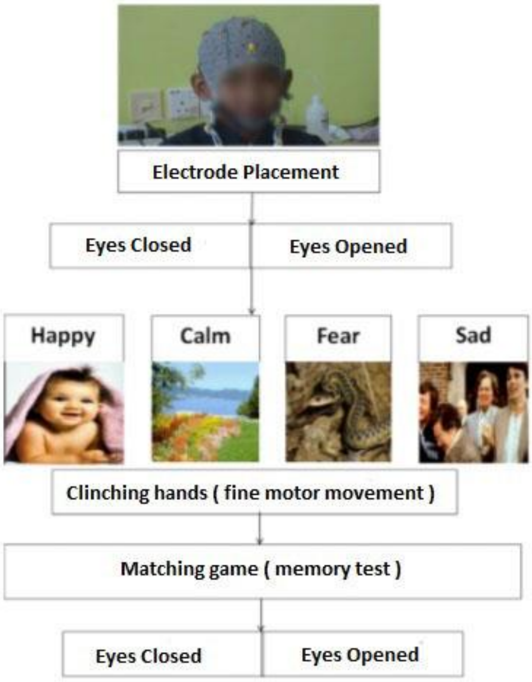

Fig. 2 Experimental Design

B. Data Pre-processing

To physically get the greatest results for epileptic patterns and reduce mistakes, essential things need to be captured and implemented. After the data gathered in the form of brain signals, before proceeding to the precursor emotional test and memory test, many technological operations must take place before a result may be obtained.

While doing the data pre-processing, we need to implement the elliptic filter [19] to remove noise from the data. Initially, ellipord creates the prototype of a lowpass filter by converting the passband frequencies of the required filter into 1 Rad/s and -1 and 1 RD/s (for bandpass and bandstop filters). It then calculates the minimal order needed to comply with the stopband requirements of a lowpass filter. Next, a user defined function is used called the Splitband function which is implemented inside MATLAB workstation [20]. The utility of this function is it splits the bandwave for each emotion data into Alpha wave, Beta wave and Gamma wave. This helps to separate the band waves into specific order according to Alpha, Beta and Gamma but as our time is limited to work on, for now we decided to work on the Alpha wave of every emotion which will help us analyze the next steps further. In brain activity, Alpha waves, which measure between 8 and 12 Hz may play an essential function and evidence indicates that they may help to reduce feelings of anxiety and sadness. Thus, calculating Alpha will help the research find out the mental state of every child including autistics

C. Feature Extraction

In this phase, we are going to be extracting out the features of every emotion data of a subject including the eyes open/closed and game data. This will assist in training the classification model ahead. Feature extraction is performed to find out the main characteristics on all 19 EEG machine channels for brain signals. We used an MFCC (Mel frequency cepstral coefficients) function to extract the characteristics, which includes categorization and aims to identify performance enhancements including a high accuracy in the training of data, before moving on to the next stage of the process which is classification. It also provides many frequency channels to analyze data.

As it has been noticed that the collection of data is in a form of complication and their complexity consists of a large dataset from numerous channels each, this step cannot be skipped as the purpose of feature extraction is to simplify the dataset to speed up the subsequent classification process.

D. Classification

In the classification section, we utilized the MLP (Multi-layer perceptron's) classifier to determine if the findings of the tested children were influenced by autism or not by their brain signals. The reason behind choosing this is it creates strong classifiers that may outperform other classifiers in terms of performance when compared to others. The result obtained via the use of the MLP function may be accessed easily in MATLAB in the category of feedforward artificial neural network type.

Brain signals from participants are extracted and trained using the MLP algorithm during an International Affective Picture System (IAPS) emotion sequence. In addition to this, for the precursor testing while eyes closed and memory testing while gaming, we utilised this classifier to determine the psychologically based autism level of every subject. The aggregate results for each subject may be regarded as a preliminary outcome and by using those results, we can come up to a conclusion including a comparison among the subjects and their emotion levels by calculating the variance and arousal. The procedure may be clearly shown in the form of a figure, which is given below:

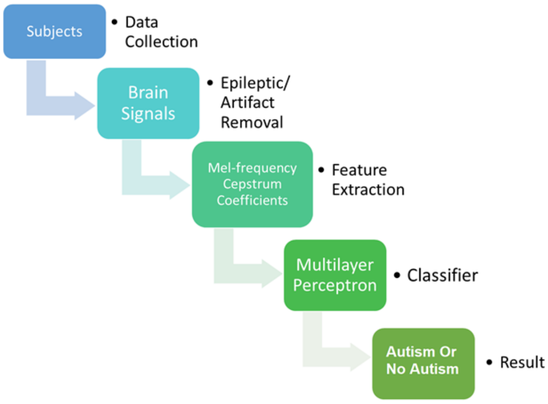

Fig. 3 Classification Technique using MLP

The amount of variance and arousal in the end will give an idea on the emotional state of every subject using the model proposed and developed by James A. Russell in his Russell's model of affect (1980) emotional state model.

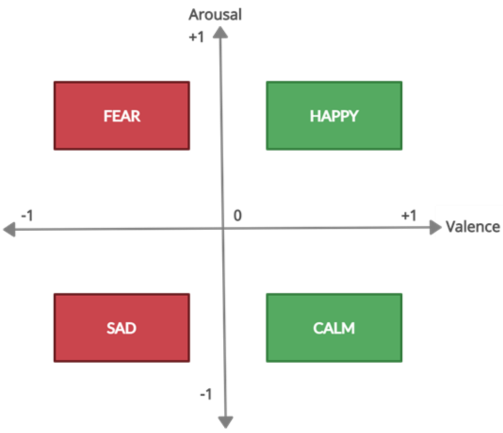

Fig. 4 Russell's model of affect Diagram

As it is seen from the diagram stated above that the Russell's theory on emotional state model includes various emotions with a varied rating for their valence and arousal values. To work with the training data, the Alpha band waves are determined for each of the emotions [21] using split-band. In addition to that, as the testing will undergo two different experiments which are precursor testing while eyes closed and memory testing while gaming. After that while the feature is extracted, we need to put the variance and arousal values for each of the emotion sets and randomize all the Alpha datasets to train data in MLP phase. After the data gets trained based on two different experiments using MLP function, the test results will then be classified based on the presence of positive or negative emotions such as sad-fear or happy-calm in the plotted valence-arousal graph. Subjects may show some autism because of their unpleasant emotions whereas on the other hand having a positive emotion indicates they may not be autistic at all.

IV. Preliminary Result Analysis

As far as the result is concerned, there are some interesting things that we came to know and visualize as well for the preliminary phase. There are two different data that have been used to inspect the difference of the outcome and these are 1) Learning disability kid Subject-1 and 2) Normal Subject-7.

A. *Learning disability kid Subject-1*

As discussed previously, there are two phases of testing that have been covered until now. Talking about the first test, which is called a precursor emotion test that involves the emotional state of a learning disability kid, shows that while their eyes remain closed, they appear to be calm at the first few seconds but as the time moves on the intensity of sadness rises and remains the same until the end. This says that they are tending to fall towards negative emotion which is not good.

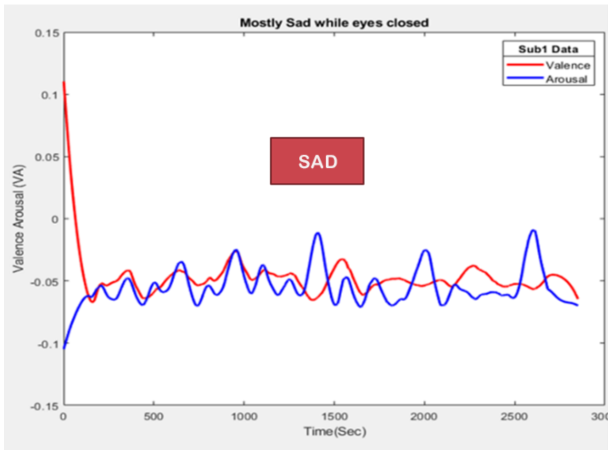

Fig. 5 Precursor emotion for learning disability kid

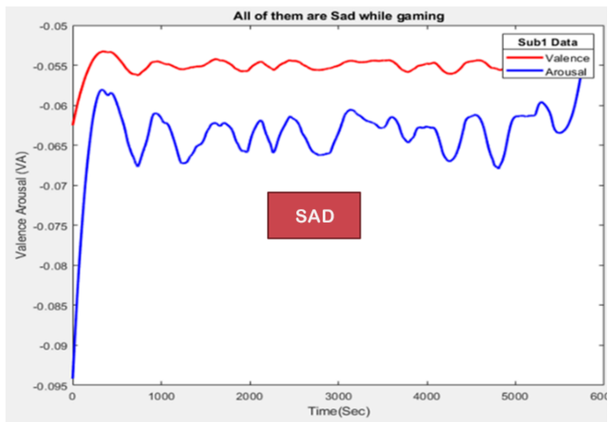

Fig. 6 Emotion for matching game (learning disability kid)

On the other hand, when talking about the memory test, it has been observed that there is no specific difference while switching to this test, as a result the emotion still carries negative indications with a VA (Variance-Arousal) value set under 0. This concludes that the learning disability kid remains sad all the time while playing the matching game.

B. *Normal Subject-1*

When it comes to the testing phase for the normal kids, the brain signals carry some different patterns and features compared to that of a learning disability kid. Arousal and valence dimensions are used to classify emotions [22]. At the time of using precursor emotion testing on a normal child, the study found that it tends to have a positive emotion as the VA (Valence-Arousal) values indicate to be calm and happy. That means a normal kid remains calm while also having a joyful emotion at the time of their eyes are closed.

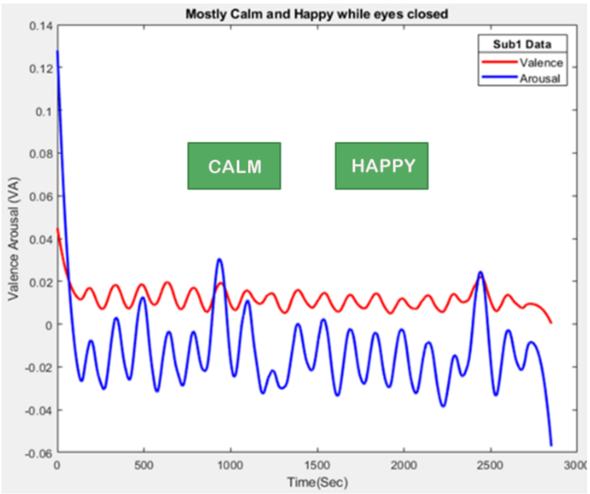

Fig. 7 Precursor emotion for normal kid

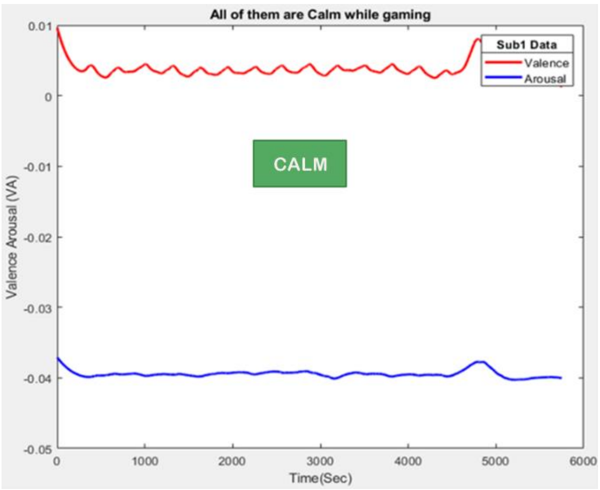

Fig. 8 Emotion for matching game (Normal kid)

In the next testing phase, which is a memory test, the study found that while playing the matching game, a normal kid is completely calm having no kinds of negative emotions involved throughout the whole process. The VA signals also indicate that a normal child has a very consistent emotion pattern in the memory testing phase that proves they have a positive emotion without any unusual emotion occurrence all of a sudden which is a good sign.

Based on these factors, it can be said that there are quite noticeable differences that have been observed throughout the whole process of testing which are not vague at all. Whether it is a memory test or precursor emotion test, there has always been an indication towards negative emotions when it comes to the testing of a learning disability kid and in contrast, an indication towards positive emotions arises when it comes to testing a normal kid.

V. Conclusions

To conclude, it has been proved that abnormal kid tends to have negative emotion which might develop autism. Negative attitudes, impoverishment and pessimism can lead to chronic signs of autism that may disturb the body's hormone balance, depletes the brain chemicals needed to make it happy. Negative emotions prevent autistic children from thinking and acting in a sensible manner, as well as from viewing circumstances from their genuine viewpoint. When this occurs, people are more likely to perceive and remember only what they want to see and remember only what they want to recall.

A. *Future Work*

For future improvement, we would work and focus on other learning disabilities. These learning disabilities will be as follows:

- ADHD (attention deficit hyperactivity disorder), which is a complex brain disorder that impacts both children and adults. It is a developmental condition that impairs the brain's executive functions and the sufferers of it have difficulties with impulse control, attention, and organization as well.
- Dyslexia which are a very common learning disability found in every country. Dyslexia is a specialized learning issue that impacts certain learning abilities such as reading and writing.

We will also be working on analysing more data because observing more data will end up giving a proper and consistent result. Hence, we will be inspecting another 10 subjects in the future work and finally, we will compare between normal and abnormal kids completely based on every learning disability type while early detecting the symptoms of having disabilities in the normal kids as well.

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