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Literature Survey on Biomedical Application using EEG Data for Detection of Multiple Health Disorders

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Abstract: The electroencephalograph (EEG) is a medical modality that plays crucial roles in detecting, displaying and recording electrical activity in the brain. This paper reviews the analysis method of EEG signal for common diseases in Malaysia which are autism, Cerebral Palsy (CP), Parkinson and schizophrenia from Malaysian and worldwide research paper that has been published. Fast Fourier Transform, Short Time Fourier Transform (STFT) and event-related potential (ERP) are some of the techniques used in analysing EEG signal were covered in this work. It can be concluded that EEG plays its role as a detection tool to detect the disease in the early stage, rehabilitation, classification or as an assistive tool for the patient according to the needs of the diseases.

Keywords: Autism, EEG, cerebral palsy, multiple sclerosis, schizophrenia

1. Introduction:

Epilepsy is a gathering of neurological problems that are portrayed by a getting through inclination to create repetitive seizures and can influence people of all ages. Epilepsy emerges from the steady neurobiological course of 'epileptogenesis' [1], which causes the ordinary mind organization to fire neurons in a self-supported hyper-synchronized way in the cerebral cortex. As per the World Wellbeing Association (WHO), 70 million individuals overall have epilepsy and epilepsy trails just headache, stroke, and Alzheimer's illness in the rundown of the most broad cerebrum sicknesses [2]. The seizures brought about by epilepsy are incapacitating and upset the everyday exercises of the patients, and are related with an expanded gamble of untimely mortality. The shortage of nervous system specialists in numerous nations confounds the administration of epilepsy particularly in the emerging nations where the nervous system specialists are hard to find.

Despite the fact that epilepsy and seizures are some of the time alluded to equivalently in some writing, it is important that not all seizures are epileptic and spasms and seizures may likewise happen because of intense neurological put-downs (like stroke, mind injury, metabolic aggravations, and medication harmfulness) without fundamentally mirroring a drawn out inclination to repetitive unmerited seizures (for example epilepsy).

An epileptic seizure (ES) is brought about by an unexpected strange, self-supported electrical release that happens in the cerebral organizations and as a rule goes on for under a couple of moments. ES assaults are difficult to foresee, additionally, seriousness and term of assault likewise can't be expected. In this way, wounds and wellbeing issues from the occasions are a main issue for patients and their families. Consequently, early expectation of epilepsy assaults is urgent to keep away from and counter their unfriendly outcomes. The mind movement of patients with epilepsy can be sorted as various states: pre-ictal (quickly going before seizure), ictal (during a seizure), post-ictal (promptly following a seizure), and (in the middle between seizures). Further subtleties of these terms are given in the part of the paper. ES forecast is a grouping issue, for example separating between the pre-ictal and interictal states. Because of the repetitive idea of epilepsy, ES happens in gatherings and patients tormented from seizure bunches can obtain advantage through the anticipating of follow-on seizures.

Electroencephalography (EEG) is an especially powerful indicative instrument to concentrate on the practical life structures of the cerebrum during an ES assault. The expectation and prescription of epilepsy have been comprehensively concentrated on through EEG. EEG signals, which are non-Gaussian and non-fixed, measure the electrical action in the cerebrum which are thus used to analyze the sort of the mind issues.

2. Related Work:

Epilepsy is a group of neurological disorders that are characterized by an enduring predisposition to generate recurrent seizures and can affect individuals of any age. Epilepsy arises from the gradual neurobiological process of ‘epileptogenesis’ [1], which causes the normal brain network to fire neurons in a self-sustained hyper-synchronized manner in the cerebral cortex. According to the World Health Organization (WHO), 70 million people worldwide have epilepsy and epilepsy trails only migraine, stroke, and Alzheimer’s disease in the list of the most widespread brain diseases [2]. The seizures caused by epilepsy are debilitating and disrupt the day-to-day activities of the patients, and are associated with an increased risk of premature mortality. The dearth of neurologists in many countries complicates the management of epilepsy—especially in the developing countries where the neurologists are in short supply.

Hidalgo-Munoz et al [3] studied EEG signals of 26 females while watching emotional images from IAPS. This study considered emotions according to the valence-arousal model. In the processing step, they used spectral turbulence (ST), a method which was inspired by ECG studies. Results show that the left temporal lobe has considerable activity during emotion elicitation.

Weinreich et al [4] measured variations of alpha frequency band in frontal lobe from an oddball paradigm. Participants were asked to describe each image regardless of the emotion of the image. 16-channel EEG signals were recorded from 20 female and 8 male participants.

Bozhkov et al [5] considered valence-arousal model for emotions and recorded EEG signals from 26 females viewing IAPS pictures. They used Echo state networks (ESN) to cluster and classify positive and negative emotions. They obtained the desired results and demonstrated the performance of their proposed method.

Li et al [6] evaluated large scale functional brain networks of depressed people and normal ones using graph theory. Participants' emotions were elicited by Ekman pictures including positive, negative and neutral emotions. Simultaneously, EEG signals were recorded from 16 depressed and 14 normal participants. In this study, EEG signals were processed by extracting coherence in frequency bands such as delta, theta, alpha, beta and gamma. Results showed that for depressed participants total coherence values in gamma band were higher than normal people. Also, total coherence among normal participants for negative emotions was higher in gamma band. Moreover, there were abnormal networks in prefrontal and occipital lobes for depressed participants.

Mavratzakis et al [7] evaluated event related potentials (ERPs) of 27 individuals during watching pictures. In this study, three picture databases were used as stimuli: KDEF (Karolinska Directed Emotional Faces Database), RAFD (Radboud Faces Database) and IAPS. After statistical analysis of ERP components, results showed that emotions did not influence on P1 component. Also, N170 increased during watching emotional pictures but N100 was not sensitive to emotion changes. Moreover, early posterior negativity (EPN) increased during watching fearful images.

Tseng et al [8] evaluated phase synchrony and EEG activation oscillation in Asperger syndrome (AS) patients while they were recognizing emotions from face images.40 AS group included 10 individuals and the normal group consisted of 10 individuals. Emotions were stimulated by pictures. Results demonstrated that AS group had no determined N400 in response to pictures, also, they showed lower synchrony in temporal and parietal-occipital lobes at delta/theta and weaker phase synchronization in separate regions of brain.

Koelstra and Patras [9] recorded EEG signals from several participants according to the valence-arousal model. They showed video clips in order to evoke emotions. In this study, power spectral density of EEG sub-bands was calculated and active units (AU) were detected from face videos of participants. Then a combination of features was applied. Hidden Markov Model (HMM) and GentleBoost were used as the classifiers. Results showed that the combination of face videos and EEG signals improved the accuracy.

Lee et al [10] proposed an emotion recognition system based on fuzzy logic. They used video clips to elicit emotions and recorded EEG signals from 12 participants. They extracted dynamic features from emotional states and 3D fuzzy GIST and 3D fuzzy tensor to extract brain features in a semantic level. Independent component analysis (ICA) was used to remove artifacts. ANFIS was used to classify emotions, results showed the performance of the proposed method.

Haung et al [11] presented a multimodal approach to recognize emotions. In this study EEG signals from MAHNOB-HCI database were used. Discriminant power spectrum and difference power spectrum were extracted from EEG signals of 27 participants. Local binary patterns (LBP) were extracted from videos of participants' faces. Then fusion in features and decisions were applied. Finally, SVM and KNN were used as classifiers. Results showed that using multimodal data, gives better recognition results.

Akar et al [12] examined brain dynamics of major depressive disorder (MDD) patients during stimulation using positive and negative emotions. They used music as stimulation. Three different situations including noisy environment, relaxation and listening to music were considered. EEG signals from 15 MDD patients and 15 normal people were recorded and analyzed using nonlinear methods. Some kinds of complexity measures such as Lempel-Ziv, Kolmogorov were calculated and then significant differences were evaluated by ANOVA measure. This study demonstrated that MDD patients have more complex EEG signals in parietal and frontal lobes comparing to normal people. Also EEG signals of these individuals had lower complexity in frontal and parietal lobes while listening to music compared to other situations.

Yuvaraja et al [13] extracted higher order spectral features from EEG signals and evaluated emotion changes between PD patients and normal individuals. EEG signals were recorded from 20 PD patients and 20 normal participants while watching video clips. Samples were classified into six basic emotions (sadness, happiness, fear, anger, surprise and disgust) through SVM classifier. Results showed PD patients have weaker emotions in comparison with normal individuals, especially for negative emotions.

Schizophrenia can be detected by emotion stimulation. Brennan et al [14] examined this hypothesis by processing ERP signals. This study used international BRAINnet database, including 108 schizophrenic patients and 108 normal cases. All individuals watched emotional pictures including sadness, fear, anger, disgust and happiness and simultaneously ERPs were recorded in conscious and non-conscious conditions. Then significant differences among 2 groups were achieved through analysis of variance (ANOVA). Results showed that schizophrenic patients had shorter brain activity, about 70 ms. Also, schizophrenic patients in response to disgust had positive shifts after 70 ms and normal people had negative shifts in response to fear and anger in comparison with happiness in temporal-occipital regions.

Yeung et al [15] examined cortical connectivity of autistic children while watching KDEF face pictures and compared them with normal children. EEG signals of 18 autistic children and 18 normal children were recorded during stimuli and then analyzed using theta coherence index (cortical connectivity index). This study showed that autistic children have deficiency in emotion recognition. Also, there was no theta coherence modulation while normal children had theta coherence modulation in the right frontal lobe in response to emotional faces. Theta coherence modulation in response to emotions is related to social deficiency of autistic children.

Psychogenic non-epileptic seizures (PNES) are unknown among epileptic seizures. Recent studies showed that PNES patients have impairments in control of their emotions. Urbanek et al [16] evaluated this hypothesis. In this study, EEG signals from 56 patients and 68 normal individuals during emotion stimulation were recorded. Results demonstrated that these patients have weaker emotions, more negative feelings and stronger control on their emotions than normal people.

Croft et al [17] detected emotion deficiency in Huntington's patients via ERPs. In this study, EEG signals from 11 Huntington's patients and 11 normal individuals were recorded while participants expressed emotions such as scramble, neutral, happiness, anger and disgust. Results showed lower accuracies for negative emotions such as disgust, neutral and anger due to decreased functionality.

Dolah et al. characterized autism by social disconnectedness; failure to identify and read the astuteness of human communication behaviours and interactions, an obsessive addiction to routines and repeatable behaviour, the repetitions of sentences and words without regard to their significance or context [18]. Since autism is a spectrum disorder, each autistic child is special and will have different characteristics from each other. Three categories of autism are mild, moderate and severe. However, some studies classify autism into three functions, Low Functioning Autism (LFA), Medium Functioning Autism (MFA) and High Functioning Autism (HFA). It is reported that in the 1970s, the rates of autism spectrum disorder was less than 3 per 10,000 children and increased to more than 30 per 10,000 in the 1990s [19]. In another study made by local survey indicated that one in every 625 children in Malaysia is autistic [18]. Current research [20] states that roughly one in every 150 children is diagnosed with some form of autism while according to Behnam et al.[21], autism affects 1 in 66 births.

Most of the research towards autism use frequency-domain and time-domains in analyzing EEG signals. However, the analysis in the frequency domain was more significant compared to time-domains technique [22]. Malaysian researcher, Sudirman et al. [23] indicates that the diagnosis of alpha value (10 Hz) using Fast Fourier Transform (FFT) in visual simulation for autistic children is lower than normal children. The Fast Fourier Transform (FFT) method is used to analyze the characteristics of the acquired EEG by power spectral density (PSD) estimation. The low value of alpha is a result of lower relaxation and insecure feeling of respondents towards his environment. It is also stated that most autistic children experienced eye disorders since the age of 3 which makes them wear spectacles and undergo eye treatment. Hoole et al. [22] came out with the results stated that the abnormalities in EEG alpha waves are related to the early age of autism. Listening to relaxing music helps increasing the alpha level and reduces the beta level in autism children.

Behnam et al. [21] discovered the EEG background activity of autisms and normal children by using Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT). By using mean and standard deviation as the extracted features, the result gives 82.4% of original grouped cases that is correctly classified. According to Wang et al [24], autistic children show abnormalities of EEG waveform in the limbic system and cerebellum. The resting EEG studies reveal that 20% of individuals with autism show epileptiform discharges at rest, commonly without the existence of clinical seizures besides an increase in alpha power coherence. There is an exception for severe autism where studies reported unaffected alpha power. Thus, an adult will have low in delta and theta frequency bands compared to children.

Alhaddad et al. [25] presented a method to diagnose the autism using Fisher Linear Discriminant Analysis (FLDA) to classify the extracted FFT features. A method using Fourier methods to extract EEG features and k nearest neighbours (kNN) in classifying between normal and autistic children shown 82.4% accuracy was presented by Sheikhani et al. in [26]. William et al. demonstrated a classification between typically developing and high-risk group autism using multiclass support vector machine and modified multiscale entropy (mMSE) as a feature vector [27]. Razali et al. applied Gaussian mixture model (GMM) to extract feature in frequency-domain and multilayer perceptron (MLP) to classify the data [28]. Further research was done by Duffy [29] to differentiate between Aspenger Syndrome (ASP) and autism disorder which shows that Aspenger diagnosis does not show symptom of impairment in communication and does not have lack of difficulty in language compared to autistic children. This result of studies is crucial as Aspenger's syndrome is always debated by researchers on whether it is a part of autism or another unique entity.

With the help of campaign and active non-government organization like National Autism Society of Malaysia (NASOM), there is an increase in awareness of autism in Malaysia for the last few years. However, more research needs to be done to give an efficient support system to families having autistic members [18].

Cerebral palsy (CP) is one of the most prevalent chronic disabling states of childhood and affected 1.2 to 2.5 per 100 school age children [30]. CP is a class of non-progressive group, motor impairment syndromes secondary to lesions or oddities of the brain that arise in the early stage of growth [31].

3. Conclusion:

The EEG is used as the analysing tool of diseases, classification and rehabilitation. The approaches of the analysing diseases also differ depending to the disorders. Time-frequency pre-processing is used in some EEG waveform analysis techniques, whereas focal waves are used by others to identify the active side of the EEG signal. EEG is widely used in Malaysia, however compared to other countries, it is still not as effective at detecting diseases. More research and development needs to be done to improve the usage of the EEG.

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