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Brain Developmental Disorders' Modelling based on Preschoolers Neuro-Physiological Profiling

Abdul Wahab[1], Norhaslinda Kamaruddin[2]
Kulliyah of Information and Communication Technology, International Islamic University Malaysia, Kuala Lumpur Malaysia
Advanced Analytics Engineering Center, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia

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ABSTRACT

Frequently misunderstood by their teachers as being low performers, children with learning disabilities (LDs) such as dyslexia, ADHD, and Asperger's Syndrome develop low self-confidence and poor self-esteem that may lead to the risk of developing psychological and emotional problems. On contrary, research has shown that a substantial number of these children are capable of learning, and hence, are high-functioning. Therefore, there is a need to provide for the early detection of LDs and instruction that focuses on their needs based on their profiles. Profiling is normally done through observations on the psychological manifestations of LDs by parents and teachers as third-party observers. The first party experience, which is reflected through brain manifestations, is often overlooked. Hence the aim of this paper is to present an alternative solution to profile young children with LDs using electroencephalogram (EEG) that capture brain signals to measure brain functionalities and correlate them with the different LDs. Studies on neurophysiological signals and their relationship to LDs are used to develop Computational Neuro-Physiological (CN-P) model to be an alternative in quantifying the children brain activation function related to learning experience. It is envisaged that such model can profile children with learning disabilities to provide effective intervention in timely manner which can help teachers to provide differentiated instruction for children with LDs. This is in line with the thrust of the Education National Key Result Area (NKRA), the Malaysia Education Blueprint 2013-2025, and the Special Education Regulations 2013.

Corresponding Author:

Norhaslinda Kamaruddin,
Advanced Analytics Engineering Center,
Faculty of Computer and Mathematical Sciences,
Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia.
Email: norhaslinda@tmsk.uitm.edu.my

1. INTRODUCTION

Brain developmental disorders can be defined as the impairment of the growth of the central nervous system especially for children from age 3 to 9-year-old. Such disorder often relates to neurodevelopmental in nature and occurs in infancy and childhood, which may include, Autism and Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), Learning Disorder or Dyslexia. Typically, children with learning disability (LD) are experiencing neurologically-based processing problem that interferes with their ability in basic psychological processes, namely: input (auditory and visual perception), integration (sequencing, abstraction and organization), memory (working, short term and long-term memory), output (expressive language) and motor (fine and gross motor). Such shortcoming in these processing problems can interfere with learning basic skills such as reading, writing and/or mathematical understanding; for instance, word reading fluency, spelling accuracy and arithmetic calculation.

Children with learning disabilities (LDs) such as dyslexia, ADHD, and Asperger's Syndrome normally have difficulties in communicating and expressing their thoughts, hence making it difficult for profiling. The symptoms of LDs are usually observed during school years and sometimes later. Moreover, some individuals may not even aware that they are having LD and do not get any help and intervention from the experts. Such situation posed as a challenge because academic ability need to be explicitly learned and taught. If it is prolonged and not well addressed, learning demands will have been increased over time and exceed the individual's limited capacities making them left out from the mainstream learning cohort and develop an absence of self-confidence.

In diagnosing a learning disability, cognitive assessment including psychoeducational and neuropsychological evaluation is important. Several psychological instruments are available to identify children with learning disabilities; and as such, the instruments are based on third party observations. The first party experience, which is reflected through brain manifestations, is often overlooked. The research and development in the utilization of brain wave patterns to study the developmental invariance in learning, however, involves huge and expensive equipments such as the functional Magnetic Resonance Imaging (fMRI) or the Positron Emission Tomography (PET). The costs, the machines availability and portability factors make it almost impossible to use in studying and profiling large numbers of children. Therefore, there is an urgent need to conduct this study to provide an alternative approach to tackle LDs early to minimize the problems that are often associated with the late detection of LDs.

Based on the hypotheses that brain wave patterns reflect the learning experience of the children in general and represents the children learning abilities and the neuro-physiological brain activities can be measured, we proposed a model of Computational Neuro-Physiological (CN-P) model to be an alternative in quantifying the children brain activation function related to learning experience using electroencephalogram (EEG). It is envisaged that such model can profile children with learning disabilities to provide effective intervention in timely manner.

This paper is organized in the following organization; Section 2 desribes relevant concepts such as learning disabilities, brain developmental disorder and neurophysiological measurements to hypothese the possibility of quantification of brain signal to complement psychologists' approach to identify pre-schoolers with learning disability tendencies. Section 3 outlines the proposed approach of Computational Neuro-Physiological (CN-P) model to realize the understanding in literature review for development of the proposed model. This paper is then concluded with discussion of future work.

2. LITERATURE REVIEW

2.1. Brain Developmental Disorder and Learning Disabilities

The developmental disorder relates to difficulties of utilizing academic skills. It has been added to the updated Diagnostic and Statistical Manual of Mental Disorders 5 (DSM-5), an instrument used by the psychologists to diagnose mental disorders. Academic skills need to be taught and learned explicitly and it is not related to the lack of education opportunities, intellectual disability or inadequate education instructions. In many cases, it is observed that children with learning disability will have poorer performance of the norm of their age on standardized achievement test within domain of difficulty.

Attention Deficit Hyperactivity Disorder (ADHD) is the most common childhood psychiatric disorder and is thought to reflect subtle abnormalities in central nervous system functioning [1]. For this reason, ADHD is being studied increasingly with a variety of brain imaging techniques including longitudinal studies. Magnetic Resonance Imaging (MRI) is particularly suitable for the study of pediatric patients, providing high-resolution images without ionizing radiation. Recent study noted inconsistencies in the ADHD neuroimaging literature and concluded that specific abnormalities have not yet been convincingly demonstrated. ADHD is associated with about a 4% decrease in volume throughout the brain. Intriguingly, this decrease is most marked in white matter of un-medicated patients. Furthermore, with the exception of caudate nucleus, suggesting that active psychiatric intervention at an early stage during childhood and adolescence are essentially healthy in ADHD, and that neuropsychiatric symptoms appear to reflect fixed earlier neurobiological abnormalities [1]. This in fact indicates an early detection and intervention of such disorder can assist the normal brain development of such disorder.

Professionals can now diagnose children with autism when they are as young as 2 years of age [2]. Screening and the role of the pediatrician have become even more critical as we have recognized the stability of early diagnosis over time and the importance of early intervention. At this point, experts working with children with autism agree that early intervention is critical. There is professional consensus about certain crucial aspects of treatment (intensity, family involvement, focus on generalization) and empirical evidence for certain intervention strategies. However, there are many programs developed for children with autism that differ in philosophy and a lack of research comparing the various intervention programs. Most of the programs for children with autism that exist are designed for children of preschool age, and not all are widely known or available. While outcome data are published for some of these programs, empirical studies comparing intervention programs are lacking.

Dyslexia is a specific learning disability that is neurobiological in origin. It is characterized by difficulties with accurate and/or fluent word recognition and by poor spelling and decoding abilities. These difficulties typically result from a deficit in the phonological component of language that is often unexpected in relation to other cognitive abilities and the provision of effective classroom instruction. Secondary consequences may include problems in reading comprehension and reduced reading experience that can impede growth of vocabulary and background knowledge. Recent research attempt to demonstrate how an understanding of dyslexia could be used to ensure that children in the school systems who are at risk of dyslexia can be identified early before a sense of failure sets in [3]. The emphasis has been on dyslexia as a dimensional disorder rather than a discrete diagnostic category with evidence showing that children having dyslexic difficulties can be helped by specific interventions underlines the need for timely action rather than waiting for diagnosis.

In all the three cases of brain developmental disorder, it is found that early detection and intervention can help fixed their neurodevelopment abilities. The detection process to date has been based on the experts (either a psychologist or psychiatrist) to perform the necessary test to perform the diagnosis. Due to the lack of experts to perform such diagnosis this program would like to recommend a prescreening system for all preschoolers such that we can ensure in this case every child to be given a chance to lead a normal life after the age of 7.

Children with learning disabilities most commonly misunderstood as low performers may develop low self-confidence and poor self-esteem that lead to the risk of developing psychological and emotional problems. However, research has shown that a substantial number of these children are cognitively able, and are capable of learning, and hence, are high-functioning. Thus, there is a need to provide for differentiated learning that focuses on their strengths and needs based on individual profiles. Because children with learning disabilities have difficulties in communicating and expressing their thoughts, the profiling is normally done based on the third-party perceptions, instead of the first party genuine experience which is reflected through the brain state manifestation.

2.2. Neurophysiological Measurement and Brain Developmental Disorder

The emergence of neuroimaging techniques has encouraged more studies that aim to understand the neurophysiology of cognitive events, including learning disabilities through affective states analysis. Statistical Parametric Mapping (SPM) was implemented to analyze fMRI data in [4]. Arousal stimuli were identified at the midline and medial temporal lobe. Valence stimuli were mediated by dorsal cortical areas and mesolimbic pathways. In different studies [5-7], using the same approaches, different neural substrates were identified to modulate affective dimensions. In [8], the left lateral frontal cortex, basal ganglia are activated when positive affect stimuli were presented. The negative affective states were observed at insula and using the brain states analysis has provided significant insights of how affective states are generated at the brain. However, such techniques are complex, by which high level neuro-scientific expertise are required. Not only the expertise is rare, but also the equipment used is also non-portable and very huge. Thus, it is not suitable to study brain activities of performing tasks that involve more dynamic movements. Thus, electroencephalogram (EEG) is considered. EEG has the advantages of being portable, cheaper and produce the highest temporal resolution.

Through affective computing approach [9-10], various machine learning techniques are employed to analyze affective states dynamic from EEG signals for different purposes, including affective state profiling. One of the studies [11] that used on 6 statistical measurements 64 channel EEG and 2 electrooculogram (EOG) as features for affective profiling produced accuracy between 50 % to 90 % using Multilayer Perceptron (MLP) classifier. Similar study was also conducted using Support Vector Machine (SVM) for profiling affective states based on EEG signals that are recorded during listening to music [12]. In different studies, brain signals are also analyzed to profile autistic children [13-14]. Other than affective state analysis, EEG signals are also analyzed to perform driver's behaviors profiling [15-16], which indicates how the stress levels affect driving behaviors on simulated conditions. However, the profiling of high-functioning children with learning disabilities for differentiated learning strategies has not been looked at. Therefore, the objective of this study is to design and develop a profiling model for children with learning disabilities from brain signals based on neuro-computational approach.

3. RESEARCH METHODOLOGY

Since the research involves the design and development of artificial artifact (computational model), the general design research model [17] is adapted as the research methodology. The model has been widely adapted in several computing studies including the investigation of textual pattern mining for text summarization [18], comparison of different agent-based solutions for information retrieval [19] and development of mobile translator using optical character recognition [20]. Based on the model, researching a design involves several phases including awareness of problem, suggestion, development, evaluation and conclusion. Figure 1 illustrates the proposed Computational Neuro-Physiological (CN-P) model based on the brain signals captured using electroencephalogram (EEG). The research methodology for this study consists of three major phases that reflect the objectives of the research. The phases are; analysis of the problem, design and development and evaluation and analysis.

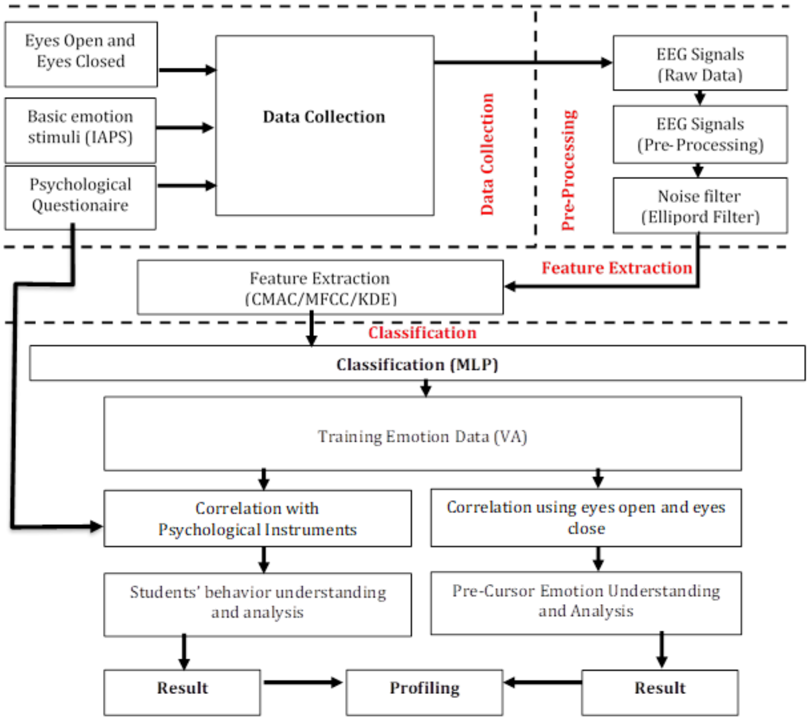

Figure 1. The Proposed Computational Neuro-Physiological (CN-P) Model

3.1. Phase 1: Analysis of the Problem

The problem of pre-schoolers profiling based on LDs is outlined. The problem statement, objective, motivation, scope and limitation as well as milestones and deliverables are deliberated. Then, literature review is conducted to strengthen the understanding of the theoretical concepts and viable solutions. Detailed discussion with subject matter expert (educationists, neurologists and psychologists) are conducted to acquire information about the problem domain including the state-of-the-art studies on learning disabilities, especially on dyslexia, ASD, ADHD and Asperger children from the perspective of education, neuroscience and psychology; as well as the computer scientists input on brain signal measurements method using both qualitative and quantitative EEG. The advantages and drawbacks of the current approaches are compared and used as a reference for the design of the proposed approach.

3.2. Phase 2: Design and Development

In the second phase, the proposed model is designed and developed. In addition, data collection is also performed. Relevant experiments are designed in such a way that it can invoke brain state for LDs identification with proper hardware and software recording brain signal acquisition. A theoretical model of Computationa Neuro-Physiological (CN-P) model is proposed. Once the theoretical model has been validated with the expert, the actual data collection is performed. The participants are asked to observe certain protocol to elicit brain activation function to test their ability in the basic psychological processes. The brain signals are captured using EEG as raw data in wav files. For validation purposes, psychological test questionnaires are also provided to determine the severity of LDs. The raw EEG signals will then be pre-processed to clean the input from unwanted artifacts such as noise and eye-blink movements. Elliport filter is used as noise cancellation method. To extract relevant features, several feature extraction methods are proposed based on our finding in literature review such as CMAC, MFCC and KDE. This is also based on our prior experience that such approach can yield comparable classification performance. The extracted features are then classified using classifier. For simplification purposes, Multi Layer Perceptron (MLP) is selected because it mimics the way the brain processes the data.

3.3. Phase 3: Evaluation and Analysis

Once the classification results are obtained, evaluation of the proposed approach is conducted. Classifier parameters tuning for optimal performance and computation time is iteratively done and recorded. The results are then compared with emotion classification because it is hypothesized that children with LDs have different emotion processing. To complete the analysis, students' behaviour understanding and analysis from psychologists and educationists approached are correlated and measured. The result is used for the pre-schoolers with LDs profiling. Such profiling is hoped to be able to perform early detection of learning disability among children.

In this paper, we present work in progress. We are currently involved in the development of theoretical model of Computational Neuro-Physiological (CN-P) model. As for now, the theoretical framework is drafted with the input from educationist and content expert. Once completed, the experimental approach of this theoretical model will be presented and discussed.

4. CONCLUSION AND SIGNIFICANT OF THE RESERACH

Some preliminary works on 14 subjects of children age 9 to 12 years old indicated the potential of using EEG for detecting ASD, ADHD and Dyslexia based on time and frequency domain analysis seems to indicate the potential of the research. A negative alpha-beta power ratio indicate a potential of ASD and a positive theta-beta power ratio could be a possible ADHD while large differences of left brain to right brain power ratio could be potential for dyslexia. Early detection of such LDs can lead to better understanding of individuals learning abilities thus making learning more effective. Since there are many studies also indicating learning effectiveness to affect thus CN-P model can provide a more comprehensive modeling of individuals with learnimng disabilities. More efforts need to be concentrated in ensuring the validity of the model. It is envisaged that CN-P model is in line with the thrust of the Education National Key Result Area (NKRA), the Malaysia Education Blueprint 2013-2025, and the Special Education Regulations 2013.

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